

Piecing the Puzzle Together: Building a Bridge to Discovery Using Health Informatics Approaches for Autism Spectrum Disorder

by

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of the requirements for the degree of
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and Center for Biomedical Informatics

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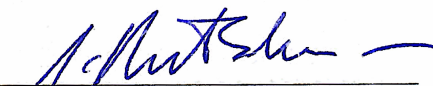
This dissertation by Katherine A. Brown is accepted in its present form by the Center for Computational Molecular Biology and Brown Center for Biomedical Informatics as satisfying the dissertation requirement for the degree of Doctor of Philosophy.

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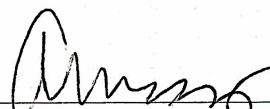

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EDUCATION

Brown University

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Biomedical Informatics

- Center for Biomedical Informatics and Center for Computational Molecular Biology
- Thesis: Using Informatics Approaches to Assess and Address Safety Needs in Pediatric Behavioral Health Conditions
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Aug 2018 – May 2024 | Providence, RI

The University of Texas at Austin

Master of Science in Nursing

Child Health/Public Health

Jun 2013 – Dec 2015 | Austin, TX

Abilene Christian University

Bachelor of Science

Biochemistry

- University Honors

Aug 2010 – May 2013 | Abilene, TX

EXPERIENCE

Brown University, Graduate Research Assistant

Aug 2018 – May 2024 | Providence, RI

- Doctoral candidate affiliated with the Brown Center for Biomedical Informatics and the Center for Computational Molecular Biology.
- Dissertation work centered around applying mixed-methods approaches in machine learning techniques and qualitative methods to investigate Autism Spectrum Disorder and other mental health conditions.
- Proficient in diverse methodologies, including data infrastructure, clinical terminologies, data standards, data processing, machine learning, natural language processing, user-centered design, qualitative user needs assessment, and digital health technology design.
- Research focuses on the Learning Health System framework, developing methodologies to transform data into actionable knowledge.
- Designing digital interventions to enhance patient care and promote interoperability between health systems and patients.
- Conducting formal evaluations of methods and technological interventions.
- Utilizing a user-centered design approach to develop tailored digital tools and resources for patients and their families.
- Dedicated to contributing to healthcare innovation through research and practical application of digital health technologies.

Lifespan Health System, Research Intern

Jan 2021 – May 2024 | Providence, RI

- Interdisciplinary collaboration between Lifespan Pediatric Emergency Services (LPBHEs) to create a comprehensive longitudinal database.
- Leverage electronic health record (EHR) data and computational approaches, enhance quality and safety measures, and develop predictive models for ED return visits.

Austin Regional Clinic, Nursing Chair/Nursing Supervisor

Feb 2015 – Aug 2018 | Austin, TX

- Oversaw urgent care operations as Nursing Supervisor in a sizable multi-specialty clinic, providing leadership and management.
- Coordinated nursing staff schedules, assignments, and oversaw workflow to ensure optimal patient care and staff efficiency.
- Provided leadership and guidance to nursing staff, addressing challenges, and promoting a positive and collaborative work environment.
- Conducted hiring and training for clinical staff in both the clinic and phone triage, serving as a valuable resource for team members.
- Collaborated with the Analytics and EHR team to enhance patient care and safety, contributing to Nursing Chair responsibilities.

- Developed and implemented standardized evidence-based practice guidelines, promoted best practices in clinical quality, and continually reviewed and revised clinical operation policies to improve patient outcomes.
- Led coordinated process improvements in multi-specialty practices, serving as a key resource for clinical operations.
- Focused on fostering a culture of excellence and implementing strategic initiatives to optimize patient care, contributing to the advancement of healthcare delivery.

Ascension Seton Healthcare, Clinical Informatics Specialist

Jul 2016 – Oct 2016 | Austin, TX

- Analyzed clinical practice workflows and identified process inefficiencies across 11 Seton Network hospitals.
- Optimized system performance and technology utilization for clinicians using Cerner COMPASS EHR.
- Conducted thorough analyses of both clinical and organizational needs.
- Designed and evaluated clinical information systems and applications to enhance efficiency and effectiveness.
- Contributed to the development of order sets and order entry fields (OEFs) in Zynx Health as a member of the Orders Team.
- Aimed to standardize care with evidence-based practices seamlessly integrated and coded within the COMPASS EHR.
- Played a crucial role in system upgrades and participated in project implementations.
- Tested new applications and provided training to staff on emerging technologies and updates within the EHR.

Austin Surgery Center, Registered Nurse

Jul 2014 – Feb 2015 | Austin, TX

- Provided comprehensive and compassionate patient care as a Registered Nurse in an interventional pain management-focused ambulatory surgery center.
- Addressed neuropathic symptoms using diverse modalities in interventional pain management-focused ambulatory surgery center.
- Executed charge nurse duties, overseeing patient care and ensuring smooth operations.
- Conducted hardware testing to maintain functionality of advanced medical equipment.
- Contributed to training new staff for proficiency in operating specialized equipment
- Committed to patient safety and quality care within established protocols.

SKILLS

• Programming Languages: Python, Julia, R	• Data Standards: OHDSI OMOP CDM, HL7 FHIR	• Clinical Terminologies: ICD-9/10-CM, SNOMED CT, CPT, LOINC, NDC, RxNorm; CCS-R, PheWAS
• JavaScript	• HTML/CSS	• MySQL
• LaTeX	• Unix/Bash/PowerShell	• Workflow Visualizations (UMLS)
• Data Analysis	• Data Visualization	• Natural Language Processing
• User-Centered Design	• Qualitative Analysis	• Focus Group/Interview Moderator
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AWARDS & HONORS

1st Place (Martin Epstein Award) - AMIA Student Paper Competition, American Medical Informatics Association (AMIA) 2023 Annual Symposium	2023
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3rd Place- AMIA Student Paper Competition, American Medical Informatics Association (AMIA) 2020 Annual Symposium	2020
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Ella Kate and Wallace Ralston Nursing Students Scholarship, The University of Texas at Austin	2014

Lee Hage and Joseph D. Jamail Endowed Scholarship in Nursing, <i>The University of Texas at Austin</i>	2013
Chemistry Dow Employees Scholarship, <i>Abilene Christian University</i>	2012
Chemistry Dow Employees Scholarship, <i>Abilene Christian University</i>	2011
Academic Excellence in Research Scholarship, <i>University of Texas Medical Branch at Galveston</i>	2011

PUBLICATIONS

- **Brown KA**, Sarkar IN, Chen ES, Sheinkopf S. Biomedical Informatics Applications for Autism Spectrum Disorder (ASD) Causes, Detection, and Early Intervention: A Systematic Review. (in preparation)
- Kim W, Donise KR, **Brown KA**, Cancilliere MK, Chen ES. Identifying and Characterizing the Transgender and Nonbinary Population Presenting to Pediatric Psychiatry Emergency Services. AMIA Informatics Summit. 2024. (accepted)
- **Brown KA**, Donise KR, Cancilliere MK, Aluthge DP, Chen ES. Characterizing Autism Spectrum Disorder and Predicting Suicide Risk for Pediatric Psychiatric Emergency Services Encounters. AMIA Annu Symp Proc. 2023.
- Aluthge DP, **Brown KA**, Crowley KM, Chen ES, Sarkar IN. Using Supervised Machine Learning to Predict Problems and Medications from Health Information Exchange Data. AMIA Annu Symp Proc. 2023. (*submitted*)
- **Brown KA**, Sarkar IN, Crowley KM, Aluthge D, Chen ES. An Unsupervised Cluster Analysis of Post-COVID-19 Mental Health Outcomes and Associated Comorbidities. AMIA Annu Symp Proc. 2022.
- **Brown K**, Donise K, Hoffman P, Chen ES. Clinical Workflow Analysis and Modeling of Pediatric Behavioral Health Emergency Service. The Patient and the Practitioner in the Age of Technology: Promoting Healing Relationships. 2021. [Abstract]
- Eisman AS, **Brown KA**, Chen ES, Sarkar IN. Clinical Note Section Detection Using a Hidden Markov Model of Unified Medical Language System Semantic Types. AMIA Annu Symp Proc 2021;2021:418–27.
- **Brown KA**, Fraser HS. How accurate is the Isabel diagnostic decision support system with patients presenting with acute symptoms of heart disease? AMIA Annu Symp Proc. 2021. [Abstract Poster]
- **Brown KA**, Sarkar IN, Chen ES. Mental Health Comorbidity Analysis in Pediatric Patients with Autism Spectrum Disorder Using Rhode Island Medical Claims Data. AMIA Annu Symp Proc. 2020;2020:263–272. PubMed PMID: 33936398; PubMed Central PMCID: PMC8075466.
- Pinchuk IV, Beswick E, Saada JI, **Wood KA**, Johnsrud AJ, Qiu S, Mifflin RC, Reyes VE, Powell DW. Colorectal Cancer Derived Cd90+ Stromal Cells Contribute to the Tumor Promoting Microenvironment via Expansion of CD4+FOXP3+IL-17+ T Cells and Suppression of TH1 Responses. AGA Gastroenterology. 2012 May 142: 5, S-32.

PRESENTATIONS

- (2023) **Student Paper Competition**, “Characterizing Autism Spectrum Disorder and Predicting Suicide Risk for Pediatric Psychiatric Emergency Services Encounters”, AMIA 2023 Annual Symposium, New Orleans, LA [November 11, 2023]
- (2023) **Conference Presentation**, “Characterizing Autism Spectrum Disorder and Predicting Suicide Risk for Pediatric Psychiatric Emergency Services Encounters”, AMIA 2023 Annual Symposium, New Orleans, LA [November 13, 2023]
- (2023) **Seminar**, “Unsupervised Machine Learning: An Overview of Methods and Case Study in Using Cluster Analysis for Studying COVID-19 Mental Health Outcomes”, Advance-CTR Machine Learning for Health Seminar Series and BCBI Health Informatics Seminar Series, Providence, RI [March 3, 2023]
- (2023) Kim, Wyatt, Donise, Kathleen R., **Brown, Katherine A.**, et al., “Identifying and Characterizing the Transgender and Nonbinary (TGNB) Population Presenting to Pediatric Psychiatry Emergency Services” (2023). Warren Alpert Medical School Academic Symposium. Brown Digital Repository. Brown University Library. <https://repository.library.brown.edu/studio/item/bdr:3fz6nkv8/>
- (2022) **Student Paper Competition**, “An Unsupervised Cluster Analysis of Post-COVID-19 Mental Health Outcomes and Associated Comorbidities”, AMIA 2022 Annual Symposium, Washington, DC [November 5, 2022]
- (2022) **Conference Presentation**, “An Unsupervised Cluster Analysis of Post-COVID-19 Mental Health Outcomes and Associated Comorbidities”, AMIA 2022 Annual Symposium, Washington, DC [November 8, 2022]
- (2021) **Conference Presentation**, “Clinical Workflow Analysis and Modeling of Pediatric Behavioral Health Emergency Services”, The Patient and the Practitioner in the Age of Technology Conference, Providence, RI [January 8, 2021]
- (2020) **Student Paper Competition**, “Mental Health Comorbidity Analysis in Pediatric Patients with Autism Spectrum Disorder Using Rhode Island Medical Claims Data”, AMIA 2020 Annual Symposium, virtual [November 14, 2020]

- (2020) **Conference Presentation**, “Mental Health Comorbidity Analysis in Pediatric Patients with Autism Spectrum Disorder Using Rhode Island Medical Claims Data”, AMIA 2020 Annual Symposium, virtual [November 16, 2020]

TEACHING

- **Web Designer & Content Creator**, BIDSS Manual (Biomedical Informatics and Data Science Skills (BIDSS) Manual, Brown Center for Biomedical Informatics [2019 - present]
- **Content Creator**, National COVID Cohort Collaborative (N3C) Virtual Short Course [2022]
- **Teaching Assistant**, BIOL 6535 Preclinical Elective: Biomedical Informatics and Data Science Skills for Medical Students, The Warren Alpert Medical School of Brown University, Providence, RI [Summer 2019-2021]
- **Teaching Assistant**, BIOL 1555/PHP 2561 Methods in Informatics and Data Science for Health, Brown University, Providence, RI [Spring 2020]
- **Teaching Assistant**, BIOL 1550 Biology of Emerging Microbial Diseases, Brown University, Providence, RI [Spring 2020]
- **Student Mentor**, Scholarly Concentration in Biomedical Informatics, The Warren Alpert Medical School of Brown University, Providence, RI [2019-present]

FUNDING

Children’s Behavioral Health and Clinical Services: Lifespan Pediatric Behavioral Health Emergency Services (LPBHES) Database, SAMHSA Jan 2020 – Jan 2025

PI: Kathleen Donise

Develop a database for the Lifespan Pediatric Behavioral Health Emergency Services to address clinical, quality, and research needs

Expanding a Statewide Realtime Monitoring System and Program to Improve COVID-19 Testing and Vaccination for High Risk Children, NIH/NIGMS Sep 2021 – Sep 2023

U54GM115677-06S2

PI: Sharon I. Rounds / Indra Neil Sarkar

Enhance a statewide system to monitor COVID-19 patterns to guide improvements in access to testing and vaccine uptake among high-risk pediatric populations.

T32 Training Grant - Center for Computational Molecular Biology, National Institute of Health (NIH) 2019 – 2021

T32 GM128596

PI: Dr. Sohini Ramachandran, Dr. Neil Sarkar

Training in Biological Data Science awarded to the Center for Computational Molecular Biology.

PROFESSIONAL SOCIETIES

HIMSS, Member 2023 – present
Healthcare Information and Management Systems Society (HIMSS), Austin Chapter

American Medical Informatics Association (AMIA), Member 2018 – present

- Nursing Informatics Working Group (NI-WG), Digital Communities Committee (2023)
- Student Working Group
- Consumer Health Informatics Working Group
- Clinical Decision Support Working Group

Association of Nurses in Graduate School, Member 2013 – 2015
University of Texas at Austin

Society of Pediatric Nurses, Member 2015 – 2018

Conference Reviewer

- AMIA Annual Symposium (2020-present)
- NorthEast Computational Health Summit (2019)

PROJECTS

- ***Thesis – “Using Informatics Approaches to Assess and Address Safety Needs in Pediatric Behavioral Health Conditions”***

As a member of Dr. Elizabeth Chen's lab within the Clinical Informatics Innovation and Implementation (CI3) Lab, my dissertation work sought to thoroughly examine the interplay between qualitative insights and computational methods, utilizing statewide clinical data, with a specific focus on children with high needs, particularly those diagnosed with Autism Spectrum Disorder (ASD). The primary objective was to identify resource needs and risk factors contributing to adverse safety outcomes in individuals with ASD. We employed a mixed-method approach, incorporating both qualitative and quantitative analyses within the overarching framework of the learning health system, which emphasizes continuous improvement by seamlessly integrating research, practice, and data-driven insights to enhance patient outcomes and healthcare delivery. The qualitative component involved engaging with key stakeholders in the ASD community in Rhode Island, seeking to understand their perspectives and needs. Simultaneously, the quantitative aspect utilized computational methods to analyze statewide clinical data, allowing us to characterize the comorbidity burden and explore safety-related health outcomes.

The specific aims were threefold:

1. Conduct a needs assessment focused on safety in ASD patients, identifying barriers to accessing resources.
2. Define and characterize risk factors for safety-related outcomes in ASD using statewide clinical data and computational methods.
3. Draw new insights from the integration of qualitative and quantitative findings, develop an implementation strategy, and determine product requirements. These outcomes were subsequently shared in a digital repository.

The culmination of these findings and insights played a pivotal role in informing the design and development of a prototype for a future technological application. This application, centered on user needs through a user-centered design approach, adopts a learning health system perspective. The ultimate goal is to create a personalized safety application tailored to the unique requirements of individuals with ASD, with a focus on enhancing overall well-being and minimizing safety risks.

- **Data Sources:**

- Qualitative Data from focus groups for caregivers of children with high needs alongside the Rhode Island Parent Information Network (RIPIN)
- Pediatric psychiatric emergency services electronic health record data (notes)
- Rhode Island CurrentCare Health Information Exchange (HIE)
- Rhode Island All-Payer Claims Database (HealthFacts RI)

- ***Expanding a Statewide Realtime Monitoring System and Program to Improve COVID-19 Testing and Vaccination for High Risk Children***

- **Quantitative Research:** Collaborating with Dr. Chen and fellow Brown faculty, I contributed to COVID-19 studies utilizing Electronic Health Record (EHR) data from the Rhode Island CurrentCare health information exchange (HIE), which feeds into the National COVID Cohort Collaborative (N3C). Our initial analysis focused on ICU status as an indicator of COVID-19 severity, aiming to identify common features among patients with more severe cases. Additionally, we explored mental health impacts post-illness using unsupervised clustering methods such as hierarchical clustering, K-modes, and self-organizing maps (SOM) to identify mental health subgroups within the positive COVID-19 population.
- **Qualitative Research:** Working alongside Dr. Rani Elwy, the Implementation Science Core Director in the Department of Psychiatry and Human Behavior, I contributed to a RADx-UP project focusing on qualitative transcript data related to COVID-19 and the Latinx community in Rhode Island. Our project aimed to identify barriers impacting SARS-CoV-2 testing access and vaccination hesitancy within this community. I played a key role in coding focus group transcripts using rapid content analysis and the Consolidated Framework for Implementation Research (CFIR) constructs. This experience provided invaluable training in qualitative methods, including planning and conducting community focus groups, analyzing transcript data, and developing skills in implementation science methodologies.

- ***Children's Behavioral Health and Clinical Services: Lifespan Pediatric Behavioral Health Emergency Services (LPBHES) Database***

- **Clinical Workflow Analysis:** The primary objective of this project was to establish a comprehensive longitudinal database for Lifespan Pediatric Behavioral Health Emergency Services (LPBHES) by harnessing Electronic Health Record (EHR) data and other sources, catering to clinical, quality, and research requirements. Given the intricate interplay of clinicians, patients, and data within pediatric behavioral health services, the initial step involved a formal workflow analysis. While one goal was to decipher data extraction methods, the broader benefits of this analysis became apparent. Clinical workflow analysis and process mining not only facilitated a deep understanding of existing processes but also pinpointed areas for potential enhancements in patient care and outcomes. This analysis provided valuable insights into the complexities of mental health pediatric services in Rhode Island. The outcomes were presented at The Patient and The Practitioner in The Age of Technology conference in January 2021, highlighting the significance of this work in advancing our comprehension of pediatric behavioral health services and potential avenues for improvement.
- **Autism Analysis:** We examined information from LPBHES on initial assessments of children in behavioral health crisis, with a particular focus on Autism. Our analysis sought to understand the characteristics of patients coming to the Emergency Department (ED) with self-harm concerns and specifically explore the differences observed in those with Autism. The ultimate aim was to create predictive models—one for encounters involving ASD and another for those without ASD—and accurately identify patients seeking ED for suicidal thoughts and behaviors. We compared the importance of different risk factors, helping us highlight distinctions and comprehend how each model behaves, considering the unique features of the two distinct groups of patients.
- **Clinical Decision Support System Evaluation – Accuracy of Isabel Diagnostic Decision Support System for Patients Presenting with Acute Symptoms of Heart Disease:**
 - During a rotation with Dr. Hamish Fraser's lab at the Clinical and Global Health Informatics Evaluation Lab within BCBI, I contributed to a project focused on formal evaluation methods for clinical decision-making tools. The study involved utilizing data on urgent cardiology admissions from a previous assessment of a heart disease diagnosis program to assess the effectiveness of the clinician-facing general diagnosis program, Isabel Pro Differential Diagnosis (DDx) Generator. The results indicated that Isabel was a valuable tool for identifying important and likely cardiac conditions. This project, coupled with ongoing efforts such as protocol standardization, automated diagnosis matching strategies, and the incorporation of natural language processing holds the potential to advance large-scale evaluation studies using real patient data extracted from Electronic Health Records (EHRs).

REFERENCES

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 - Associate Professor of Health Services, Policy and Practice, Brown University
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 - Associate Professor of Medical Science, Brown University
 - Associate Professor of Health Services, Policy, and Practice, Brown University
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Kathleen Donise, MD

- Director, Lifespan Child Emergency Psych Services
 - Associate Professor of Psychiatry and Human Behavior, Clinician Educator, The Warren Alpert Medical School of Brown University
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Rani Elwy, PhD

- Professor of Psychiatry and Human Behavior, Professor of Behavioral and Social Sciences, Brown University
 - Founding Director of the Brown Research on Implementation and Dissemination to Guide Evidence Use (BRIDGE) Program
 - Co-Director of Implementation Science in Advance-RI Clinical Translational Research
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Hamish Fraser, MBChB, MSc, FACMI, FIASHI

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Abstract

Abstract of “Piecing the Puzzle Together: Building a Bridge to Discovery Using Health Informatics Approaches for Autism Spectrum Disorder” by Katherine A. Brown, Ph.D., M.S.N., R.N.; Brown University, May 2024

Children with high-needs, including those with Autism Spectrum Disorder (ASD), require extensive medical, behavioral, and educational support due to their complex conditions. These challenges necessitate innovative data-driven approaches to inform decision-making and improve care. The Learning Health System (LHS) framework systematically incorporates data-driven insights and evidence-based knowledge into healthcare practice to enhance patient outcomes.

This dissertation focuses on the knowledge discovery aspect of LHSs by using a mixed methods approach, combining qualitative insights and computational findings to inform a tailored healthcare intervention. The three aims are to: (1) Conduct an in-depth qualitative study with caregivers of children with high-needs to examine unmet needs, social challenges, emotional impacts, and essential resources; (2) Use computational methods to study the ASD population and associated comorbidities using statewide clinical data; and, (3) Integrate the qualitative and computational findings to create a comprehensive strategy for a technology-based application that addresses the identified needs. This overall approach strengthens the basis for more informed healthcare technologies and supports the LHS principle of continuous, evidence-based improvement.

The findings highlight the need for enhanced mental health support and personalized care plans, specifically focusing on the increased risk of suicidal thoughts and behaviors in individuals with ASD. The combined research findings further inform a concept and mockup for a digital safety plan application that addresses mental health safety and provides customized resources, aiming to improve access to necessary services for high-needs children and ASD. By integrating diverse

research outputs, design and functionality of targeted technological solutions can be improved, leading to more effective and personalized health interventions.

The components of this dissertation introduce a nested framework within the larger LHS paradigm for knowledge discovery in healthcare, emphasizing the bridge of qualitative insights and computational findings. The proposed Bridge to Discovery in Learning Health Systems (BD-LHS) framework showcases an integrated approach, leveraging the combination of stakeholder insights and computational data analysis to drive evidence-based interventions. This holistic approach aims to generate a responsive, adaptive healthcare system that meets community needs and sets a new standard for interdisciplinary collaboration in health informatics, fostering continuous improvement in health outcomes.

Acknowledgments

As I embarked on the transformative adventure of pursuing my doctorate at Brown University's Center for Biomedical Informatics and Center for Computational Molecular Biology in Providence, Rhode Island, I was welcomed by a community of remarkable individuals. My time at Brown has been nothing short of incredible, enriched by the dedication and support of numerous mentors, faculty members, staff, and fellow students. Their collective expertise in research, clinical practice, and informatics has been instrumental in providing me with invaluable learning opportunities and experiences.

First and foremost, I want to express my deepest gratitude to my primary advisor, Dr. Liz Chen. Her extensive knowledge of informatics has opened my eyes to the vast possibilities within the field. From our first meeting, Liz inspired me with the expansive realm of informatics, and we connected over shared interests in child health and mental health. Since then, her guidance has profoundly shaped both my professional growth as a scientist and my personal development. Liz possesses a remarkable depth of knowledge and a passion for setting ambitious goals while also instilling a practical approach to achieving them. I am immensely grateful for her encouragement and patience throughout my doctoral journey. Our weekly meetings have been a source of inspiration and are aspects of my doctoral experience that I cherish deeply.

I also want to extend my gratitude to Dr. Neil Sarkar, a member of my committee and the first person I contacted when my interest in informatics was sparked. Neil has been a great source of inspiration to me as an informatician. I vividly recall our initial conversation about health informatics. This discussion not only introduced me to the field of biomedical informatics but also highlighted the impactful work being done at Brown and throughout Rhode Island. I am grateful for the opportunity to have joined the early stages of the exciting initiatives that Liz and Neil were spearheading at BCBI. It is not lost on me how fortunate I have been to collaborate with outstanding clinical teams and to have access to diverse data sources that are not commonly available to many researchers. The partnerships and relationships fostered

by Neil and Liz have been crucial in these endeavors, and looking back, I am truly amazed by the wealth of opportunities that have come my way!

I would also like to express my heartfelt gratitude to Dr. Rani Elwy, another member of my committee, whose unique and vital perspective significantly enriched my work. Rani introduced me to conducting qualitative research and the critical role of implementation science in creating meaningful changes in healthcare. Working with her was an absolute pleasure; her enthusiasm and support were invaluable throughout my PhD journey. Additionally, I am immensely thankful for Dr. Kathleen Donise, who brought her extensive clinical expertise to my committee. Her invaluable clinical insights and dedication to behavioral health have made a profound impact on children across Rhode Island. Witnessing her commitment and the remarkable work she does daily at Lifespan, I am constantly inspired by her ability to handle the challenges of working with children in behavioral health crisis. Kathleen exemplifies the special kind of dedication and resilience required in such a challenging field. While I had always valued interdisciplinary collaboration, Kathleen and Rani's involvement deepened my appreciation for its significance. Thank you to the amazing PES team at Lifespan, working with Dr. Donise, Dr. Mary Kathryn Cancilliere, Wyatt Kim, and others has been a remarkable experience. Their clinical expertise and passion for the field have influenced this entire dissertation.

I am grateful to the faculty, staff, and students at BCBI for their support and the wealth of resources they provided. Dr. Hamish Fraser for teaching me the critical importance of formalizing and standardizing evaluation methods, which is incredibly pertinent in today's rapidly evolving landscape. Hamish also generously introduced me to key members of the informatics community, enriching my network and experiences immeasurably. Tarah Johnson, whose guidance in grant writing and navigating BCBI's processes was invaluable. Benny Rodriguez, who ensured events always proceeded without a hitch, and to Karen Crowley, whose enthusiastic support and cheerleading were always a source of motivation. Aaron Eisman welcomed me from day 1 with a campus tour during my visit, instilling in me a deep love for Brown. As we journeyed through grad school and into parenthood together, he was the fellow student I

always went to for feedback, and he consistently reminded me to ground the work in the clinical questions and implications. I appreciate Dilum Aluthge for his methodological guidance and ability to simplify complex computational challenges. Ryan Buckland for emphasizing the importance of mental health research. Nick Jones for offering valuable feedback during lab meetings and advice on career transitions. Vivek Ramanan consistently brought encouragement to our lab meetings, always ready to brainstorm and tackle questions. Jillian Lai helped me navigate the complexities of unsupervised learning. Grace Smith provided the qualitative expertise that was crucial for my research. Finally, I must acknowledge Ashlin Harris, Mounika Thakkallapally, Jonah Bradenday, and Farahnaz Maroof at BCBI for their expertise in data management and their efforts in building infrastructure and fostering partnerships. Each of these individuals has played a significant role in my doctoral journey, and I am profoundly thankful for their contributions.

A special thanks to all the faculty, staff, and students within CCMB. To the DGS, Dr. Sohini Ramachandran, Dr. Erica Larschan, Dr. Daniel Weinreich, and Dr. Jeff Bailey, who provided great feedback and encouragement each semester. Sohini for offering me a position on a training grant and for her exceptional guidance during the early stages of the program, which helped me sharpen my scientific communication and presentation skills and refine my specific aims and goals. Nathanael Gardener was the first friendly face I encountered in Providence, and he warmly welcomed me into the program. Maria Cardone played a crucial role in organizing and preparing everything for my defense, ensuring that all requirements were met for my graduation. I also extend my thanks to the cohort I started with: Aaron Eisman, Alan Denadel, Jeremy Bigness, Qing Wu, and Pinar Demetci. Their support through coursework and navigating life as a grad student was indispensable. Additionally, I had the pleasure of working with other CCMB students over these last few years, who enriched my experience. Sam Smith deserves a special mention for helping me devise the inspirational title for my Autism research project, "Piecing the Puzzle Together." Finally, thanks to Elsie Gibson and Chib Nwizu for their expertise and guidance in comp bio courses.

Last but certainly not least, I owe profound gratitude to my family and friends and their unwavering support throughout this journey. My husband, Matt, has been my pillar—believing in me and providing the courage to tackle what sometimes felt impossible. His role as an amazing father and partner, deeply committed to our two boys, has allowed me to pursue my dreams relentlessly. His work and passion as a behavior teacher for children with emotional needs has inspired my own work. To my wonderful boys, Beckham and Oliver, who joined our family during this journey, being their mom is my greatest joy and motivation. My mom, a constant role model, tirelessly helps others and providing steadfast support, from helping me keep my house and life in order, to being a comforting presence in challenging times. To my Dad and Leizl, who have been incredible sources of support throughout my graduate studies. From a young age, my dad instilled in me the importance of creative and “out of the box” thinking. He nurtured my scientific curiosity, teaching me how to ask the right questions and emphasizing the significance of giving it my all in everything I do. My in-laws, Brian and Leah, have been supportive in all our endeavors and as wonderful grandparents to my boys. I hold a special tribute in my heart for my late grandparents, who continue to inspire me. My Grammy instilled a love for the nature and outdoors, which has been vital for my decompression and well-being. My Papa never met a stranger, and his positive outlook on life and his mantra to “kill them with kindness” guides me daily. My sister Gracie and brother-in-law Brian have been a tremendous support, especially in aunt and uncle duties as I spent countless hours in the final stages of dissertation writing and defense preparation. Gracie’s resilience and authenticity have taught me to value hard work and embrace my true self. My brother Zach has shown me the importance of love and faith. My brother-in-law and sister-in-law, Phil and Laura, exemplify generosity, with Laura being one of my greatest cheerleaders and someone I look up to. Finally, I extend my deepest thanks many others and my entire “village” of family and friends whose collective support has brought me to this point. I am endlessly grateful for each of you.

for my boys

Matt, Beckham & Oliver

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Chapter 1: Introduction

List of Chapter Acronyms

ADHD	= Attention-Deficit/Hyperactivity Disorder
ASD	= Autism Spectrum Disorder
BD-LHS	= Bridge to Discovery in Learning Health Systems
CDC	= Centers for Disease Control and Prevention
CFIR	= The Consolidated Framework for Implementation Research
DSM-5	= Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
ED	= Emergency Department
EHR	= Electronic Health Record
ERIC	= Expert Recommendations for Implementing Change
HIE	= Health information Exchange
IDD	= Intellectual and Developmental Disabilities
LHS	= Learning Health System
PTSD	= Post-Traumatic Stress Disorder
SOM	= Self-Organizing Map

Preface

This chapter serves as the foundation of this dissertation, laying the groundwork for a comprehensive exploration into enhancing healthcare for high-needs pediatric populations, with a particular focus on autism spectrum disorder (ASD). It emphasizes the importance of using health informatics approaches, leveraging Learning Health Systems (LHS) as the core framework, amidst the growing prevalence of ASD and the complex needs of these children. Through a mixed-methods approach, this chapter introduces a framework aimed at integrating qualitative and quantitative insights to inform the design and implementation of targeted technological interventions. By setting the stage with a case study, the chapter illustrates the gaps in current healthcare for ASD individuals, emphasizing the dissertation's aim to develop evidence-based, personalized solutions that address the unique challenges faced by these patients and their families. This introduction reveals the significance of the research, targeted populations, and approaches used, outlining the dissertation's objectives and contributions.

1.1 Case Study

At the beginning of this dissertation, I introduce a 15-year-old adolescent who identifies as female and has been diagnosed with Autism Spectrum Disorder (ASD), ADHD, anxiety, PTSD, along with experiencing abdominal pain and migraines. Following an intentional overdose of Tylenol, she was taken to the Emergency Department (ED). Her recent behaviors include elopement from school and increased withdrawal from usual activities, signaling a deepening emotional distress she struggles to communicate. Despite presenting as calm and cooperative during her ED evaluation, she exhibits signs of withdrawal, limited eye contact, and a noticeable detachment from her surroundings. She discloses feelings of hopelessness and guilt, alongside challenges with sleep and significant weight loss over the past year. She was admitted to a specialized inpatient unit for individuals with autism, where she received targeted treatment. Following her inpatient care, she was discharged to outpatient services, equipped with a comprehensive set of resources and a personalized safety plan.

This case study introduces the critical importance of providing continuous, specialized support for autistic individuals facing mental health crises, ensuring they receive the care needed to navigate their challenges effectively. There is a critical need for tailored interventions in crisis situations, especially for individuals with autism, where conventional signs of suicidal behavior may be misunderstood, potentially leading to tragic outcomes. This story highlights the need for better understanding of autism and mental health outcomes in addition to specialized care approaches that address the unique needs of this population.

1.2 Significance

Children with high-needs represent a critical and growing subset of the pediatric population, requiring significant medical, educational, and behavioral support¹⁻³. These children, due to various conditions including developmental disorders, chronic health issues, and complex behavioral needs, require a multidisciplinary approach to care that addresses their unique challenges and supports their overall well-being. Among this diverse group children with special healthcare needs, individuals diagnosed with ASD

have a broad spectrum of clinical presentations, ranging from communication barriers to social-emotional deficits⁴.

Recent estimates by the Centers for Disease Control and Prevention (CDC) in a 2020 survey indicate that ASD affects approximately 1 in 36 (2.8%) children and diagnosis rates have increased 317% since the year 2000 when the estimated prevalence rate was 1 in 150^{5,6}. This rising prevalence demonstrates the urgency for approaches to better understand and address the challenges associated with ASD. Children with ASD face a higher rate of comorbidities and a reduced life expectancy compared to their peers in the general population, highlighting a significant public health concern⁷⁻¹⁵. The high prevalence of mental health comorbidities among these individuals further emphasizes the critical need for patient safety and the mitigation of health disparities^{13,16}.

Predictive tools and strategies for risk stratification can aid in enhancing outcomes for this population due to the complexity of ASD, characterized by varied presentations and severities^{17,18}. Investigating comorbidity profiles and characterizing safety outcomes are helpful in the process to designing and tailoring interventions for this population's needs¹⁹⁻²⁴. The challenges many families face in accessing effective and affordable mental health treatments for their children with ASD, point to a broader issue of resource allocation and support within communities²⁵.

Leveraging real-world health data from sources such as medical claims, electronic health records (EHRs), and health information exchanges (HIEs), these data can offer invaluable insights into understanding ASD within the context of high-needs populations. The application of data mining and machine learning techniques to analyze health data can identify unknown patterns and characterize risk factors associated with mental health comorbidities and safety-related adverse health events. Addressing safety concerns, such as aggression, self-harm and suicidal thoughts and behaviors, is essential in developing interventions aimed at improving patient outcomes^{8,24,26-38}. Through mixed methods approaches that combine community engagement with the analysis of health data, a more comprehensive understanding of needs can be achieved, guiding the design, implementation, and evaluation of clinical interventions^{39,40}.

Technological innovations have shown promise in positively impacting patient outcomes including behavioral health^{41–44}. However, ensuring the effectiveness, sustainability, and user acceptance of these interventions remains a challenge. The use of approaches in health informatics, user-centered design, and implementation science can improve the usability and compliance of clinical interventions^{45–47}. Engaging key stakeholders and analyzing clinical data to develop tailored interventions are important steps toward empowering patients, enhancing resources, and decreasing health disparities among high-needs children, particularly those with ASD^{48,49}.

This dissertation uses a mixed methods approach and introduces a nested methodological framework that forms a bridge between qualitative and computational research findings, grounded in the principles of a Learning Health System (LHS) approach^{50–56}. LHSs focus on the iterative integration of research and practice, leveraging diverse data sources and analytical methods to continuously transform healthcare^{57,58}. The proposed nested framework, Bridge to Discovery in Learning Health Systems (BD-LHS) seeks to prioritize insights gained from key stakeholders and in parallel conduct computational analyses of clinical data that can then be integrated and converted into actionable knowledge. This integration supports the prioritization of community needs, ultimately aiming to improve health outcomes. By synthesizing qualitative insights with computational analyses, this work aims to direct the development of a technological safety plan application that is evidence-based and contextually sensitive to the unique challenges faced by children with high-needs, focusing specifically on those with ASD⁵⁹. By adopting such a strategy, the deployment of resources is optimized to effectively pinpoint safety issues, mitigate access barriers, enhance patient and family engagement, and bolster communication across interdisciplinary healthcare teams.

The discovery phase of the LHS framework is essential for developing and implementing technological tools and interventions within healthcare⁵⁰. This phase focuses on identifying unmet needs in the healthcare ecosystem that technology could address and understanding the factors that influence the successful adoption and use of these technological solutions. In this work, the newly introduced framework integrates

qualitative methodologies engaging the local community with computational analyses of statewide clinical data. This multifaceted approach aims to understand the community's needs and barriers, characterizing the burden of mental health comorbidities, and addressing safety-related health outcomes. It focuses on identifying priorities, needs, and specific product requirements for the development of a personalized technological safety application⁶⁰. The BD-LHS framework can be implemented to foster a healthcare system that is both reactive and adaptive, continuously learning from and adjusting to the evolving needs of its community. The efficacy of this framework is rooted in its capacity to convert analytical findings into practical measures, culminating in the deployment of resources that are not just grounded in evidence but are also closely aligned with the unique requirements of the community it intends to serve. This can lead to improved outcomes and effective design and implementation of interventions.

The goal of this study is to analyze how integrating insights from focus groups with caregivers of children with significant needs and computational analysis of statewide clinical data can identify resource requirements and risk factors for adverse safety outcomes in patients with ASD and other mental health issues. This integrative approach emphasizes the importance of combining human-centric insights with large-scale data analysis to inform the development of targeted, effective interventions within the LHS framework, ensuring that technological advancements are both meaningful and impactful in addressing the specific challenges faced by those with ASD and related mental health conditions. The dissertation aims to provide an analysis of how health informatics approaches can be harnessed to meet the complex needs of children with ASD, thereby making a significant contribution to the field and to the lives of those affected by this condition.

1.3 Populations

The scope of this dissertation encompasses two distinct yet interrelated populations: (1) children with high-needs and (2) individuals with ASD. The dissertation predominantly focuses on ASD, but also engages with the broader category of children with high-needs, for example carrying out focus groups with caregivers from this wider group. This focus reflects the significant representation of ASD within the high-needs

category and allows for a deeper exploration of the specific challenges and interventions pertinent to this group. The research on ASD provides critical insights into the care of high-needs children, potentially informing broader healthcare strategies and addressing a crucial segment of this population.

Children with High-Needs

Children with high-needs represent a diverse group requiring specialized healthcare needs and educational services. These children often face chronic and multiple health conditions, including physical, developmental, emotional, or behavioral difficulties that exceed those of the general pediatric population^{1,3,61,62}. Their conditions necessitate a multidisciplinary approach to care, often involving a coordinated effort across various healthcare providers, educational specialists, and community resources.

Children with special healthcare needs encompass a wide array of conditions that require tailored medical, educational, and familial support^{2,63}. Developmental disorders, a key segment within this population, include a range of conditions such as ASD^{4,64}. In addition to ASD, developmental disorders also cover intellectual and learning disabilities, speech and language disorders, and motor skills disorders, each presenting unique challenges in cognitive, social, and adaptive functioning⁶⁵. Mental health conditions also constitute a significant component of the high-needs category. These may include anxiety disorders, depression, ADHD, and more severe psychiatric conditions such as schizophrenia or bipolar disorder, which can affect a child's daily functioning and quality of life⁶⁶. Intellectual and Developmental Disabilities (IDD) represent another group under the high-needs umbrella⁶⁷. This category includes conditions such as Down syndrome and Fragile X syndrome and children with these types of conditions may have limitations in adaptive behavior and intellectual functioning⁶⁸.

Other children with high-needs could include those who may require more intensive medical interventions and healthcare services due to conditions like severe asthma, diabetes, epilepsy, or cancer. These children may need frequent hospitalizations, specialized therapies, and complex medication regimens, often requiring integrated care from multidisciplinary teams³. Each of these conditions require specialized

interventions and resources. The children and families navigating these challenges often encounter a healthcare system that is fragmented and difficult to navigate. This shows that there is a need for coordinated care approaches that are sensitive to the high level of demand placed on caregivers and the complex nature of the children's needs. The care complexity for these children is compounded by factors such as socioeconomic status, family dynamics, and the availability of community resources. Caregivers often report facing significant challenges in navigating healthcare systems, advocating for educational accommodations, and securing necessary support services⁶⁹. Children identified as high-needs are not classified with this label as a medical diagnosis. Instead, this categorization acknowledges the unmet needs they may face in addition to their need for an elevated level of care to support their development and well-being. While they do not receive this label as a medical diagnosis, this dissertation adopts widely recognized diagnoses from existing literature to describe and characterize this group.

Autism Spectrum Disorder

ASD is often included in the category of high-needs children due to the significant and diverse range of support required for individuals with this condition. Children with ASD often require specialized healthcare services, educational accommodations, and family support to manage daily activities and optimize development⁷⁰.

ASD is a neurodevelopmental condition characterized by varying challenges in social communication, repetitive behaviors, and limited interests⁴. The term 'spectrum' in ASD emphasizes the wide range of abilities and challenges experienced by these individuals. Some may require substantial support in their daily lives, while others may live independently and have notable talents or skills. The diagnostic criteria for ASD, as outlined in the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5), include persistent deficits in social communication and social interaction across multiple contexts⁴. The diagnosis of ASD is based on two main criteria: (1) challenges in social communication and interaction, and (2) restricted and repetitive behaviors, interests, or activities⁷¹. The first domain manifests as challenges in social reciprocity, difficulties with nonverbal communicative behaviors used in social interaction, and

impediments in developing and maintaining relationships. The second domain is characterized by at least two of the following: (1) stereotyped or repetitive motor movements, (2) an excessive adherence to routines, (3) highly specific and intense interests, (4) and significant hyper- or hypo-reactivity to sensory input. These criteria highlight the multifaceted nature of ASD, requiring an evaluation of symptoms across both domains for diagnosis.

The prevalence of ASD has risen in recent years and continues to be a need in research aimed at understanding the etiology, developmental trajectories, and effective interventions for this condition. Interventions for ASD are diverse, often including behavioral therapy, speech and occupational therapy, and personalized educational plans⁷². Caregivers play a crucial role in the management of ASD, often becoming advocates and experts in their child's care, working closely with healthcare professionals to optimize outcomes⁷³. The role of technology has also become increasingly significant in providing new avenues for intervention and support for individuals with ASD⁷⁴.

In this dissertation, ASD serves as the primary population of interest. Given the high demand for specialized services and the potential for technology to significantly improve the quality of life and health outcomes for individuals with ASD, this dissertation aims to propose and design technological solutions tailored to this group. The research within this dissertation will explore the intersection of health informatics, implementation science, and the specialized needs of children with ASD. It will consider the broader implications of these findings for health systems, policy, and practice, with the goal of improving healthcare delivery and outcomes for the ASD population.

1.4 Approaches

This section introduces and provides an overview of the framework and approaches this dissertation focuses on. It uses various methodologies and approaches within the LHS framework, emphasizing the enhancement of healthcare delivery for high-needs children and those with ASD. Central to the LHS framework are two core competencies, health informatics and implementation science, which together form

the foundation of the strategies used throughout^{75,76}. These methodologies can help drive improvements in patient care by leveraging data-driven insights and evidence-based practices, ensuring that the dissertation's objectives are aligned with the overarching goal of fostering a responsive and evolving healthcare ecosystem⁵³.

Learning Health Systems

The LHS framework is adopted as the foundational framework for this dissertation. It was initiated by the Institute of Medicine in 2007 and represents an approach aimed at improving healthcare quality by efficiently and effectively incorporating research findings into clinical practice^{77,78}. This concept is anchored in the principle that a healthcare system should not only rely on historical knowledge and practices but should also continuously evolve by learning from new data and experiences⁵³. This model is designed to foster a culture of continuous improvement and equity in healthcare by integrating scientific research, data analytics, and patient and family engagement directly into the care process^{52,79,80}. Central to the LHS framework is the creation of a self-enhancing cycle where patient data and experiences are continuously translated into new knowledge, which is then applied to enhance healthcare delivery. This foundational principle has inspired a range of theoretical models, from simple iterative processes to complex systems involving numerous elements, highlighting the LHS's potential to transform healthcare through ongoing learning and adaptation^{50,57,81–84}. LHSs represent an approach to healthcare that emphasizes the integration of data and experiences to foster continuous improvement in health outcomes, patient care, and health policy formulation^{50,56}. The framework is characterized by a cyclical process that involves the collection, analysis, and application of data to inform and refine healthcare practices⁸⁵. This process is supported by the integration of health informatics and implementation science to facilitate the translation of data into actionable knowledge and the implementation of evidence-based interventions in clinical settings⁷⁶.

The cyclical process of the LHS includes data collection, data analysis, implementation, and an evaluative feedback loop⁸⁶. Data are gathered from a variety of sources, including but not limited to clinical data such as from EHRs, patient-reported outcomes, and operational metrics⁵⁴. This step ensures an understanding of

patient needs, healthcare processes, and outcomes⁸⁰. The collected data are analyzed to extract meaningful insights and generate evidence-based knowledge. Advanced analytics, including statistical methods and machine learning algorithms to identify patterns and trends in large clinical datasets and develop models that can assist clinicians in practice. The insights and knowledge derived from data analyses are applied to design, test, and refine interventions and practices⁸⁵. This involves the development of clinical guidelines, decision support tools, and policy recommendations aimed at enhancing healthcare delivery and patient outcomes. The implementation of interventions generates new data, which are then fed back into the system. This feedback loop enables the continuous assessment and optimization of healthcare interventions, ensuring that the system adapts to new evidence and evolving patient needs⁸⁷.

Figure 1.1 [*adapted from Flynn et al. (2018) and the University of Michigan*⁵⁴] is a visual representation of the LHS framework as a continuous, cyclical process starting from data collection, through knowledge generation, and finally to implementation in practice to create change. This figure emphasizes the integration of health informatics and implementation science approaches to create a sustainable health practice. The cyclical process includes the following nine steps⁵⁴:

1. **Collect Data:** This step involves the systematic gathering of health-related data from diverse sources, which may include medical claims, HIEs, EHRs, patient registries, and direct patient inputs.
2. **Process Data:** Once collected, the data must be processed, which involves validation, cleaning, and structuring to make it suitable for analyses. This step ensures data quality and usability.
3. **Analyze Data:** The processed data are then analyzed using various statistical, computational, and machine learning methods to uncover patterns, trends, and insights.
4. **Interpret Results:** The results must be interpreted in the context of clinical significance and potential impact on health outcomes.

5. **Represent Knowledge:** Knowledge representation involves the structuring of interpreted data into formats that are accessible and understandable, such as clinical guidelines, decision support tools, or technological solutions and interventions.
6. **Manage Knowledge:** This includes the storage, retrieval, and dissemination of knowledge within the health system to ensure it is accessible when and where it is needed.
7. **Apply Knowledge:** The managed knowledge is applied to make informed decisions or to develop solutions such as health technology tools or systems.
8. **Change Practice:** This refers to the actual implementation of new knowledge into everyday clinical practice, which can involve changing behaviors, practices, or policies.
9. **Evaluate Outcomes:** After implementation, the outcomes are evaluated to assess the impact of the changes on health outcomes, patient satisfaction, and system efficiency.

The central element, 'Health Problem of Interest', acts as the focal point, ensuring that the cycle remains patient-centered. This cycle is enveloped by the broader core competencies of health informatics and implementation science, highlighting the interdisciplinary approach required to translate data into practice effectively and the importance in facilitating each step of the LHS^{75,76}. Health informatics is important for managing and analyzing the vast amounts of data, while implementation science ensures that the insights gained are effectively translated into practice. The implementation science phases emphasize the pre-implementation and implementation phases align with the data processing and analysis, and knowledge management and application take place during implementation for sustainability⁸⁸⁻⁹⁰.

The LHS framework described here is central to the dissertation and focuses on the "data to knowledge" or "knowledge discovery" piece of the LHS framework⁹¹⁻⁹³. These steps are critical in transforming raw health data into actionable knowledge, which then influences practice and policy decisions. The dissertation will delve into how health informatics tools and techniques can facilitate this transformation in the context of LHSs. The knowledge discovery process involves data analysis techniques, including statistical analysis

and machine learning, to uncover patterns, trends, and associations within the data⁹⁴. By concentrating on this aspect of the LHS, the dissertation aims to highlight the importance of leveraging and combining community perspective with computational methods to enhance the understanding of health data and ultimately improve patient care and health outcomes.

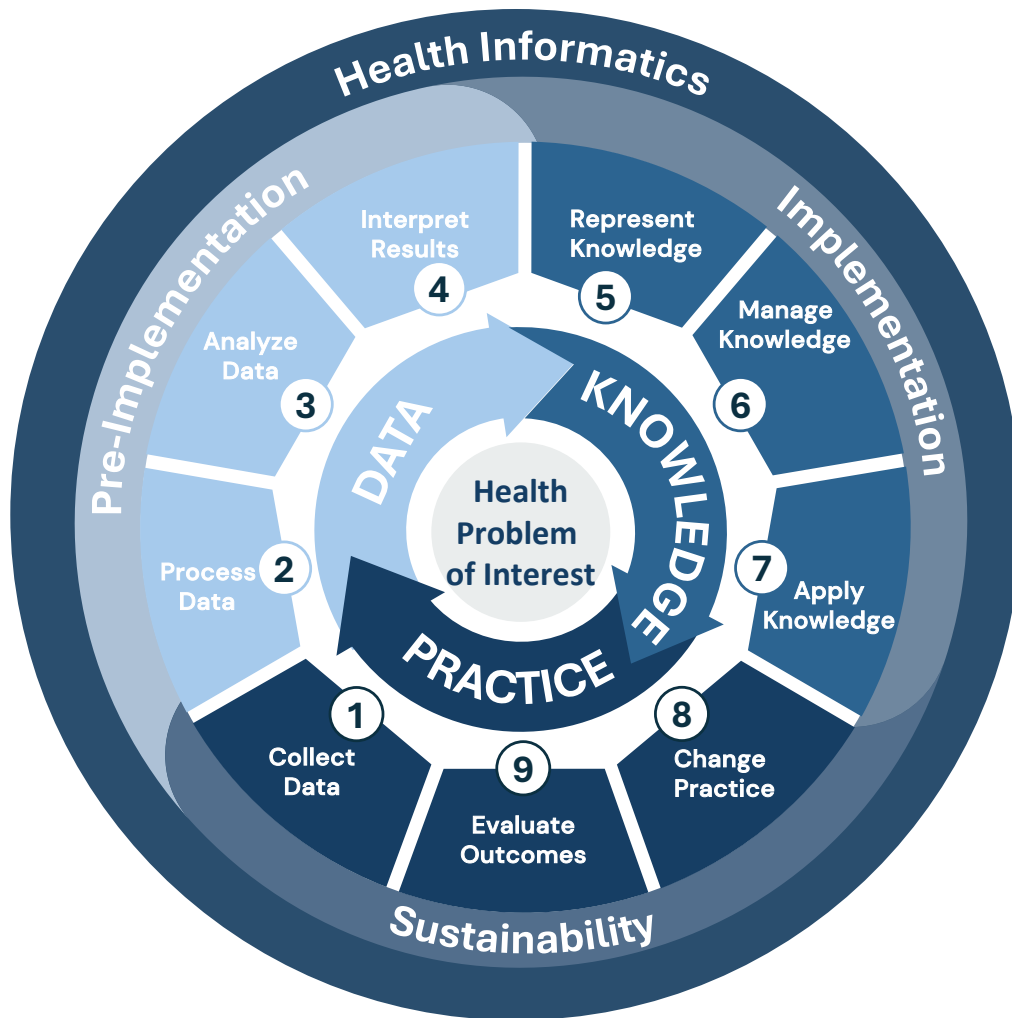


Figure 1.1: Integrative Framework of Learning Health Systems: From data collection to informed practice through core competencies of health informatics and implementation science.
[Adapted from Flynn et al. (2018) and the University of Michigan⁵⁴]

Health Informatics

Health informatics is a multidisciplinary field that blends computer science, information science, and healthcare, focusing on the tools, technology, and strategies necessary to enhance the collection, storage, retrieval, and application of information in biomedicine and health care⁹⁵. This discipline involves the computerization of health care data and technological solutions. A LHS relies on serving as the foundation for data collection, analysis, and application⁷⁶. It enables these systems to learn from every patient and to use this knowledge to deliver better care. LHSs leverage informatics approaches to process vast amounts of data from diverse sources, such as EHRs, medical imaging, and genomic information. This integration of data informs decision-making and policy development, fostering a cycle of continuous improvement in patient care and outcomes.

Biomedical informatics is a field integrates computer science and information technology to handle and analyze biological and health data, driving progress in research, diagnostics, and patient care. It focuses on the use of information technology in the understanding of health and disease and in the delivery of healthcare services^{96,97}. As illustrated in **Figure 1.2**, the field broadly covers several areas. The two main areas are translational bioinformatics and health informatics. The Venn diagram visualizing the areas of biomedical informatics can illustrate how these domains—translational bioinformatics, health informatics, and other sub-domains—overlap and interact. This visual representation highlights the integration of data, information, and knowledge across these areas to support health improvements. **Translational bioinformatics** applies principles of informatics to convert molecular data into clinical applications, enhancing the understanding of biological processes⁹⁸. **Health informatics** includes clinical informatics and public health informatics and is a discipline that combines information science, computer science, and healthcare^{99,100}. **Clinical informatics** is the field that involves the use of information technology and data management strategies to improve healthcare outcomes. It focuses on the optimal use of information and communication tools to enhance the delivery of patient care, as well as the storage and retrieval of biomedical data¹⁰¹. Clinical informatics strives to improve healthcare delivery by enhancing the clinician's

workflow, facilitating care coordination, and promoting patient engagement through technologies such as EHRs and telehealth¹⁰². It also employs artificial intelligence methods such as data science and machine learning to study complex health questions with clinical data. **Public health informatics** is the discipline that uses data science and technology to improve population health outcomes by optimizing prevention strategies, boosting health promotion efforts, and enhancing disease surveillance and emergency response¹⁰³. Public health informatics integrates digital tools and analytical techniques to advance public health research and streamline health practices.

Clinical research informatics concentrates on creating and refining informatics approaches and technologies that streamline clinical trials and research processes to improve patient treatment outcomes¹⁰⁴.

Imaging Informatics is another segment of biomedical informatics, addressing the capture, analysis, management, and storage of medical imaging data^{105–107}. It contributes to diagnostics, treatment planning, and research, enhancing the use and interpretation of imaging within healthcare. Notably, clinical research informatics and imaging informatics extends its relevance across both health informatics and translational bioinformatics, serving as a bridge that enhances both the clinical application of imaging data and its role in understanding biological processes at a molecular level.

Consumer health informatics aims to empower patients and healthcare consumers by making health information accessible and usable, fostering an environment where individuals can actively participate in their healthcare management^{108,109}. This field particularly intersects with clinical informatics and public health informatics within the larger umbrella of health informatics, facilitating a shared space where patient engagement and public health awareness converge through digital platforms. Consumer health informatics strives toward informed decision-making, health literacy, and personalized healthcare, with the goal of making health information accessible to everyone^{110–113}.

In this dissertation, health informatics approaches are central to the methodology. These approaches enable the systematic analysis of health data to derive meaningful insights that can inform healthcare policy, clinical practice, and public health initiatives. The research conducted relies on the principles of health

informatics to integrate and analyze data from clinical settings and community insights, aiming to address complex health challenges through informatics solutions. By focusing on health informatics, this dissertation showcases how informatics approaches can be used to create more efficient, effective, and patient-centered healthcare systems.

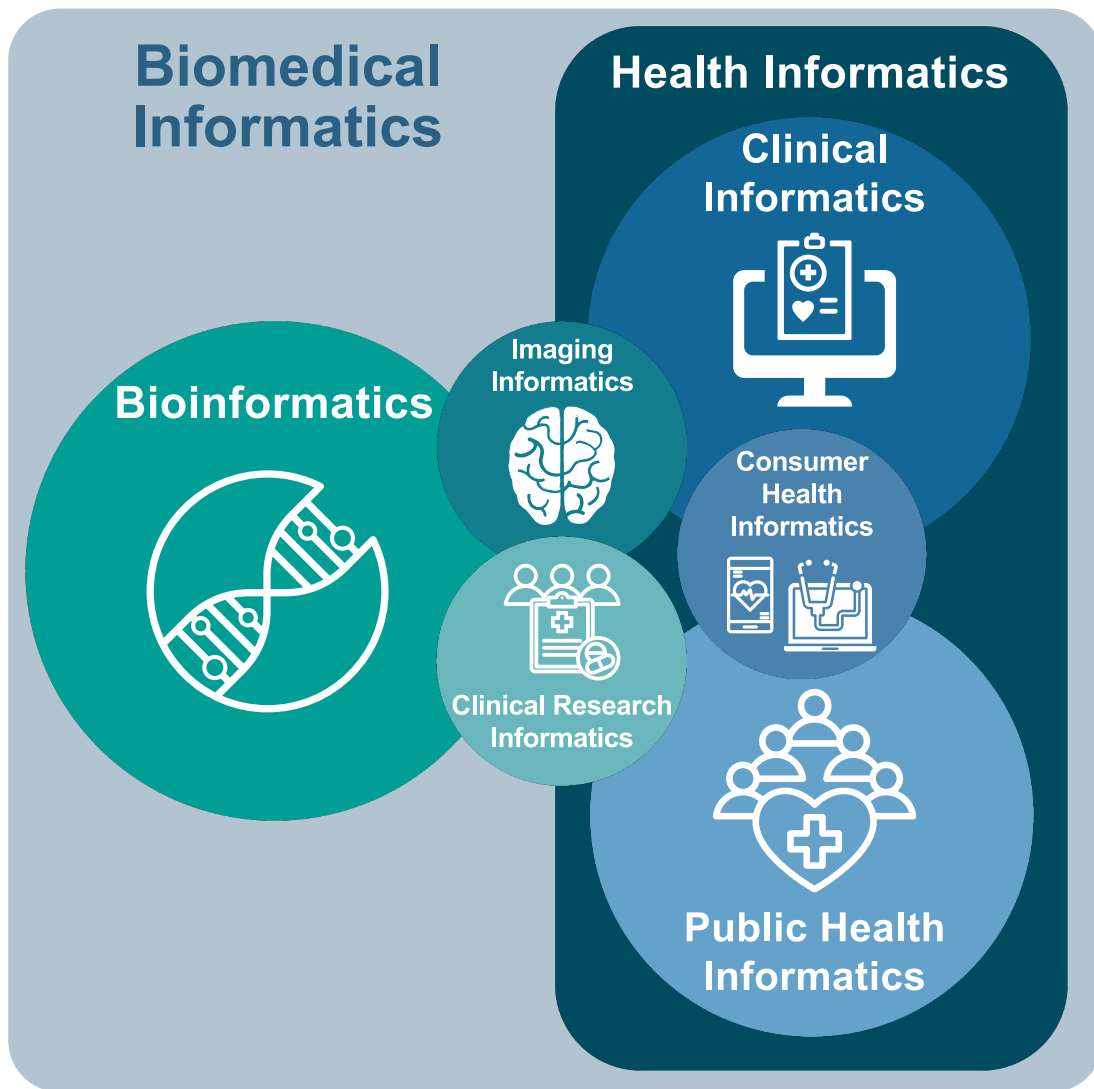


Figure 1.2: *Interconnected Domains of Biomedical Informatics, showcasing the relationship between Health Informatics, Translational Bioinformatics, and other sub-disciplines, including Clinical Informatics, Imaging Informatics, Clinical Research Informatics, and Public Health Informatics.*

Implementation Science

Implementation science is another integral component of LHSs, which are designed to continuously improve by systematically incorporating research findings into practice. As depicted in the LHS diagram in **Figure 1.1**, implementation science circles the core of the LHS, signifying its role in ensuring that evidence-based interventions are effectively translated into routine healthcare practice through the cycles of pre-implementation, implementation, and sustainability^{89,90}. It is the bridge between research and practice, enabling health systems to become learning-oriented by applying scientific methods to promote the uptake of research findings⁸⁸. Implementation science investigates how to effectively integrate research evidence and evidence-based practices into healthcare to boost service quality and effectiveness^{88,114,115}. It emphasizes the importance of healthcare workers' and stakeholders' behaviors in the lasting implementation of these practices¹¹⁶. The goal is to determine the effectiveness of interventions, who benefits from them, under what conditions, and how they can be tailored and upheld in specific contexts¹¹⁷.

Several approaches and frameworks central to implementation science are incorporated into this dissertation to strive towards successful adoption of healthcare technologies and interventions. A mixed methods approach in implementation science offers a methodology for integrating quantitative and qualitative research methods. This approach allows for the collection and analysis using computational methods to measure the impact and prevalence of certain outcomes, while also gathering qualitative data to explore the context, meaning, and factors influencing those outcomes^{60,118,119}. This approach provides a deeper understanding of the multifaceted nature of healthcare implementation issues.

The Consolidated Framework for Implementation Research (CFIR) and the Expert Recommendations for Implementing Change (ERIC) provide structured approaches to understanding and facilitating the implementation process. CFIR offers a systematic approach to address the complexities of implementing interventions in health systems. **Figure 1.3** depicts an overview of the CFIR framework encircled by the implementation cycle. It is a guiding framework for conducting qualitative research in diverse settings, enabling a deeper understanding of the factors influencing implementation success¹²⁰. It includes constructs

such as intervention characteristics, inner and outer setting, the individuals involved, and the process of implementation¹²¹ (**Figure 1.3**). ERIC, on the other hand, is a compilation of strategies identified by experts to facilitate the implementation of evidence-based practices¹²². These strategies provide guidance on how to overcome barriers to implementation and promote the adoption of innovations in healthcare settings^{123,124}.

In the development of a technological intervention, implementation science methods are used to inform the design, deployment, and scaling of applications. These methods ensure that technological interventions are acceptable, usable, and fits within the existing workflows of the healthcare setting¹²⁵. Using frameworks like CFIR and ERIC, the implementation strategy involves assessing the needs of the users, barriers and facilitators to use of the app within the healthcare setting, and best practices for training and support¹²⁶. This ensures that the app is designed with the end-user in mind, leading to greater adoption and sustained use in practice¹²⁷. By applying implementation science methods, this dissertation provides strategies for how to systematically introduce and integrate a digital tool into healthcare settings to improve patient outcomes and health system efficiencies.

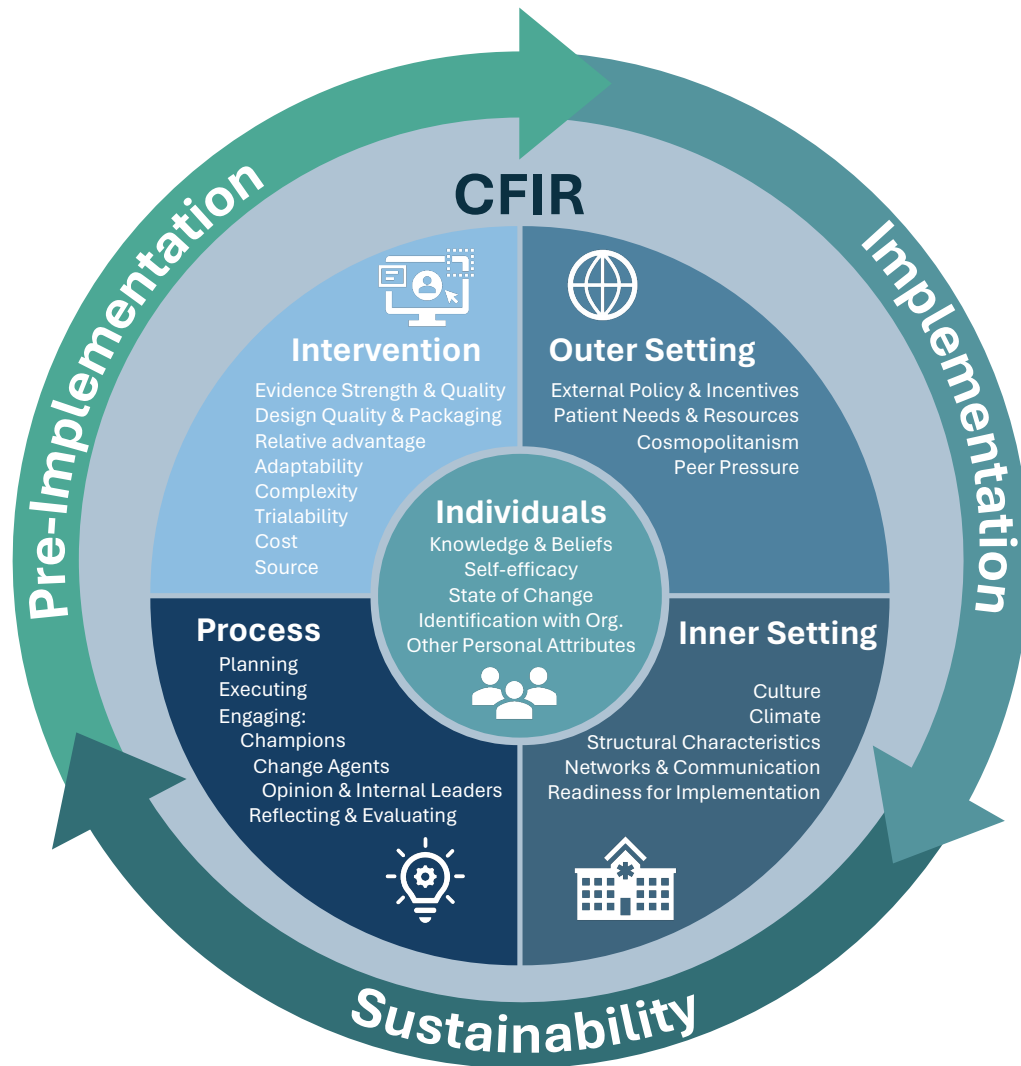


Figure 1.3: Consolidated Framework for Implementation Research (CFIR) Diagram -
 Illustrates the CFIR model, organized into a circular flow with three main components: Pre-Implementation, Implementation, and Sustainability. It is divided into five domains: Intervention, Outer Setting, Inner Setting, Individuals, and Process, which influence both the implementation and sustainability of projects. The circular arrows emphasize the ongoing and iterative nature of the implementation process.

1.5 Bridge to Discovery in Learning Health Systems (BD-LHS)

This section introduces the BD-LHS, a nested framework within the LHS paradigm, proposed through the lens of a convergent mixed methods approach. It will outline the BD-LHS framework's steps and processes, detailing the methodologies within each step: qualitative methods, computational methods, and integration of findings. This description will illuminate how the BD-LHS contributes to the advancement of LHS by harmonizing diverse research strategies.

Introduction

LHSs aim to transform healthcare through a continuous cycle of learning and improvement. However, the integration of diverse research methodologies to inform this cycle remains a significant challenge. BD-LHS addresses this gap through a nested framework that brings together qualitative research with computational methods to achieve a better understanding of healthcare challenges and gain knowledge to inform technological solutions. This nested framework highlights the importance of interdisciplinary collaboration, bringing in key stakeholders from the community and healthcare settings and used in a combination of methods from various fields such as informatics, data science, and implementation science with the goal of transforming data into actionable knowledge to improve health outcomes through continuous learning. The BD-LHS framework aligns with the overall goals of the LHS by leveraging specific methodologies and approaches to deepen the understanding of healthcare challenges and develop more effective solutions. Incorporating such a framework within the LHS allows for targeted focus on areas of interest or concern, facilitating more precise and impactful interventions. It exemplifies how the LHS framework can be adapted and expanded with nested frameworks to address complex healthcare issues through collaborative approaches.

Convergent Mixed Methods

This nested framework pulls on a convergent mixed methods design, where qualitative and quantitative data are collected simultaneously and then integrated to augment the findings. By integrating both data

types, the goal is to draw on the strengths of each method to gain a deeper understanding of the complexities of the population in question. Using a convergent mixed methods approach, qualitative and quantitative data are collected during the same stage and then integrated and compared to each other for interpretation (**Figure 1.4**)^{60,118,119,128}. The advantage of this method is that through combining knowledge and findings from both data analyses, a more holistic picture of the needs and barriers can be captured based on the strengths, weaknesses, and biases of each source of data¹²⁹. The goal is to identify how the data converge, diverge, or complement one another, which can lead to well-rounded findings¹³⁰. The integration of data happens through a variety of processes, such as a side-by-side comparison in a joint display, a narrative discussion, or through data transformation, where qualitative data are quantified, or quantitative data are qualified to facilitate comparison¹²⁸.



Figure 1.4: *Convergent Mixed Methods Approach*

BD-LHS refines the convergent mixed methods approach by specifically focusing on integrating insights from various studies and data sources centered around similar health topics. Unlike traditional mixed methods that might combine quantitative and qualitative data within a single study, BD-LHS extends this integration across different studies, leveraging diverse data sources to uncover insights⁶⁰. This methodological approach facilitates a deeper understanding of health issues by combining findings from separate research endeavors, aiming to inform more effective and successful technological interventions that are directly responsive to identified healthcare needs and gaps. By integrating qualitative studies with computational analyses on shared health topics, the BD-LHS approach aims to boost discovery and yield

better outcomes in healthcare practices, embodying the principle that the combination of computer-generated insights and human understanding is greater than the capabilities of either alone¹³¹.

Framework Overview

BD-LHS represents a focused area within LHS that employs a mixed methods approach to enhance knowledge discovery. **Figure 1.5** visually illustrates the BD-LHS framework as a dynamic and integrated process within the broader context of the LHS cyclical model. At the core of this figure, the BD-LHS framework is depicted as a nested cycle that intersects with the larger LHS loop, emphasizing the continuous interaction between the two. The visual transition from the LHS cycle to the BD-LHS framework is marked by arrows, suggesting the flow of insights and findings from the nested framework back into the larger LHS cycle to inform and enhance healthcare outcomes and healthcare technologies. The figure serves to represent the BD-LHS framework's position within the LHS, demonstrating how it refines and extends the LHS's capacity for transformational impact on healthcare through the integration of diverse research methodologies and stakeholder perspectives. The methodological approach of BD-LHS unfolds in a structured sequence, as delineated in the following steps:

1. **Qualitative Insights:** Drawing from disciplines such as user-centered design and implementation science, BD-LHS emphasizes the importance of understanding the human dimensions of healthcare. This involves in-depth analyses of patient and provider experiences through needs assessments, focus groups, and interviews with key stakeholders.
2. **Computational Findings:** Using computational methods from computer science, statistics, and data science, BD-LHS analyzes clinical data to identify patterns and predictions. This quantitative analysis complements qualitative insights, providing a scalable understanding of health challenges.
3. **Integration and Interpretation:** BD-LHS integrates qualitative and computational data analyses to inform technological interventions, enhancing knowledge and practice within LHS through a synthesis of insights.

This approach uses insights from various studies and data sources related to a specific health topic. By integrating diverse findings, BD-LHS aims to deepen the understanding and address complex health challenges, enabling the development of targeted interventions that meet the needs identified across different research efforts.

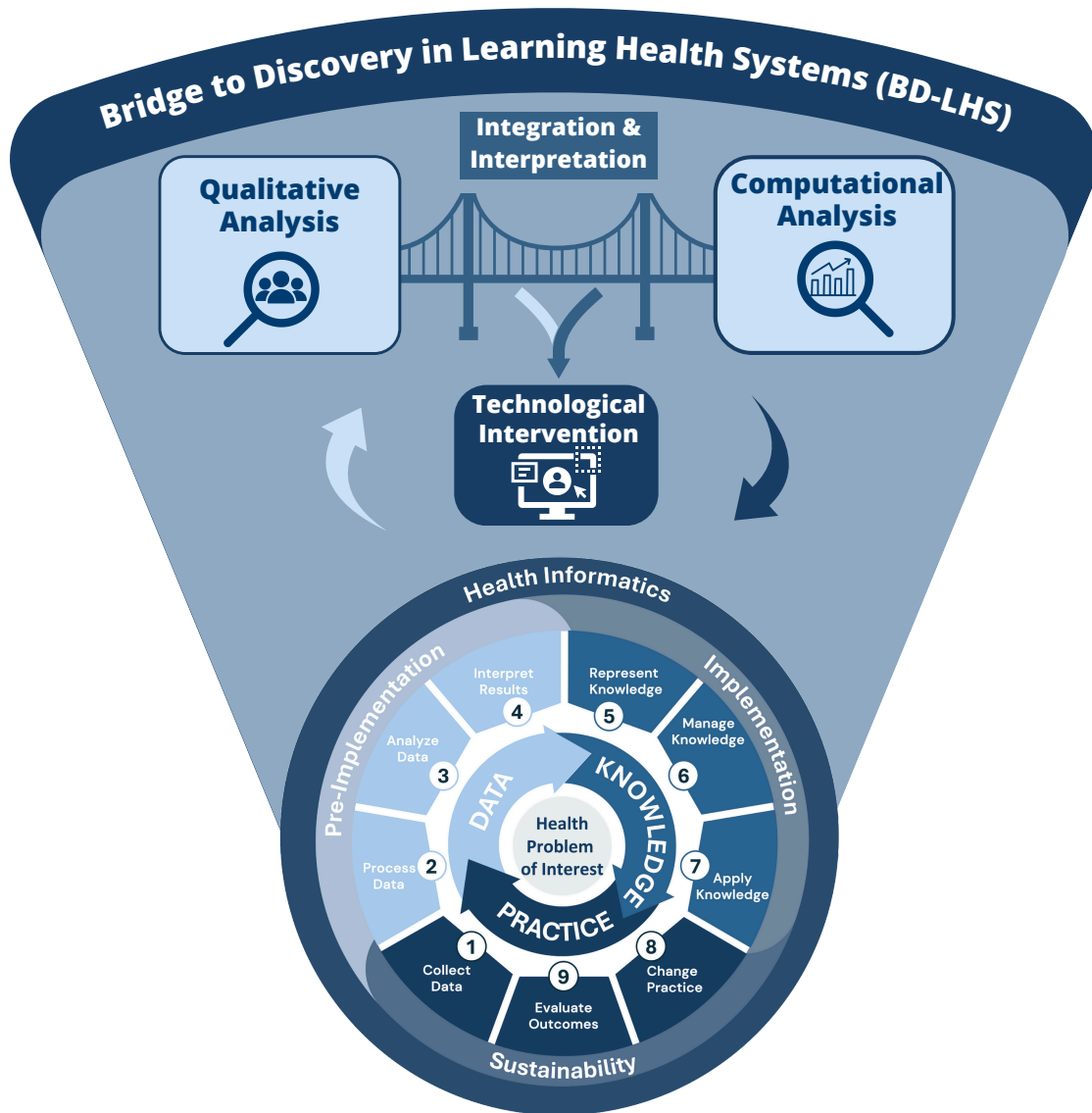


Figure 1.5: Visualization of the BD-LHS Framework within the LHS—highlighting its role in the integration of mixed methods research to enhance continuous learning and healthcare improvement. [bottom cycle adapted from Flynn et al. (2018) and the University of Michigan⁵⁴]

Qualitative Methods

Qualitative data collection for this dissertation included conducting focus groups with caregivers of high-needs children and employing a directed content analysis guided by CFIR alongside a thematic analysis. This methodology sought to capture caregivers' experiences within CFIR's five domains: (1) intervention characteristics, (2) outer setting, (3) inner setting, (4) characteristics of individuals, and the (5) implementation process^{121,132}. Structured focus groups facilitate a better understanding of community needs, barriers to service access, and caregivers' social and emotional concerns, systematically analyzed to identify key factors influencing implementation success. Audio-recorded discussions are transcribed and analyzed both thematically and deductively, categorizing themes according to CFIR domains to highlight patterns and determinants of effective implementation, ensuring findings are actionable and aligned with implementation science principles.

In addition to the CFIR-guided directed content analysis, a general thematic analysis was employed to further explore the qualitative data. This approach allows for the identification of themes and patterns that emerge naturally from the data, beyond the predetermined CFIR framework. Thematic analysis is versatile and provides a rich, detailed, yet complex account of data. It involves coding the data in phases to discover underlying ideas, assumptions, and conceptualizations^{133,134}. This method complements the CFIR-guided analysis by offering insights that are grounded directly in the caregivers' experiences, adding depth and breadth to the understanding of the issues at hand.

Incorporating qualitative methods into this dissertation, particularly through focus groups and thematic analysis, directly supports the qualitative phase of the BD-LHS framework. This approach emphasizes the importance of identifying unmet needs and understanding the experiences of caregivers to inform the development of necessary technological solutions. By including caregivers' perspectives, this qualitative investigation offers insights into the specific challenges and requirements that technological interventions in healthcare must address. This focused examination ensures that the solutions proposed are grounded in real-world experiences and tailored to meet the needs identified through the caregivers' narratives.

Computational Methods

Clinical data can be analyzed using computational techniques, including machine learning, to uncover patterns, predict outcomes, and guide healthcare decisions¹³⁵. These techniques span from straightforward statistical analyses to algorithms that model data relationships, thereby enhancing personalized medicine and public health strategies. Statistical analysis offers insights through descriptive statistics and inferential tests, highlighting trends and associations among demographic, clinical, and treatment variables¹³⁶. Beyond traditional statistical methods, machine learning algorithms—both unsupervised and supervised—advance this analysis by managing high-dimensional data and revealing patterns not immediately apparent through standard statistical approaches¹³⁷.

Unsupervised learning, with a focus on clustering, can identify inherent groupings within data, crucial for the study of conditions characterized by their complex and high-dimensional nature. Self-organizing maps (SOMs) stand out in this domain by transforming data into two-dimensional maps, thereby grouping the data to detect patterns and relationships¹³⁸⁻¹⁴⁰. Supervised learning, on the other hand, emphasizes classification and predictive modeling as essential tools for understanding risk factors and health outcomes^{137,141}. This approach uses algorithms designed to forecast specific health outcomes based on input data. Computational methods offer a toolkit for analyzing clinical data, from basic statistical insights to advanced machine learning techniques. These methods facilitate a deeper understanding of patient populations and health outcomes, highlighting the importance of both unsupervised and supervised learning in healthcare research and decision-making¹⁴².

Incorporating these computational methods into the dissertation aligns with the BD-LHS framework's goal of leveraging data analysis to advance LHS. This alignment highlights the dissertation's contribution to developing a more data-driven, evidence-based approach to healthcare, enhancing the ability to address complex health challenges and improve patient outcomes.

Integration Methods

The core feature of the BD-LHS framework is integrating qualitative insights with computational analysis to identify data and findings that converge, diverge, or complement each other. This integration provides a multifaceted view of the research problem, facilitating a deeper understanding of the population's needs and barriers. Employing a mixed-methods approach enables the triangulation of data, thereby enhancing the validity of findings and guiding the development of tailored interventions¹⁴³. Such an approach generates actionable insights that can inform clinical practice, ultimately leading to a more responsive and effective healthcare system.

Several mechanisms and methodologies can be used to achieve a cohesive, interdisciplinary synthesis of data, ensuring the development of both insightful and evidence-based interventions. This dissertation employs a combination of narrative discussion, parallel data analysis, triangulation, comparison tables, and joint displays to integrate and compare findings, thereby informing and providing goals for the concept of a technological application. Parallel data analysis conducts qualitative and quantitative data collection and analysis separately but simultaneously^{130,144}. It compares or relates the results in the interpretation phase to draw conclusions that reflect the combined insights from the disparate findings. Narrative discussion involves a detailed description and analysis of how the findings from each method complement, contradict, or enrich each other¹⁴⁵. Through narrative discussion, implications of the findings can provide a richer context for the data and draw more refined conclusions. Triangulation uses both qualitative and quantitative data to validate or corroborate findings across the two approaches¹²⁸. This method enhances the credibility and validity of the research by showing that different data types lead to similar conclusions. Comparison tables systematically organize data by themes or specific research questions, facilitating side-by-side evaluation of findings from diverse methodologies. This approach highlights data convergence and divergence, and identifies knowledge gaps, guiding further investigation and intervention development¹⁴⁶. Joint displays visually merge qualitative and quantitative findings, promoting direct comparison, contrast,

and synthesis^{130,147,148}. These visualizations aid in discerning patterns, relationships, and discrepancies, enhancing understanding of the health issue¹⁴⁹.

Other methods for integration include data merging, data transformation, and meta-matrices. Data merging techniques combine qualitative and quantitative data sets into a single dataset. This can involve creating integrated databases where, for example, qualitative themes are linked with quantitative scores or variables to facilitate combined analysis¹²⁸. Data transformation techniques convert qualitative data into quantifiable formats and vice versa, allowing for statistical analysis of qualitative themes and narrative synthesis of quantitative outcomes¹³⁰. A meta-matrix compiles and organizes both qualitative and quantitative data across multiple dimensions, such as stakeholder perspectives, intervention outcomes, and contextual factors^{150,151}. This tool facilitates multidimensional analysis, improving decision-making in intervention design and implementation¹⁵². By applying these integrative methods, BD-LHS ensures that interventions are grounded in multi-faceted insights from large datasets and aligned with the dynamic needs and preferences of the community. This synthesis of qualitative and computational analytics fosters a holistic understanding of health systems, propelling the development of interventions that are both effective and responsive to the landscape of healthcare.

BD-LHS sets itself apart by transcending traditional mixed methods research, enabling the integration of findings from disparate studies, systems, and conditions. This approach facilitates interdisciplinary collaboration and aligns well with the iterative, self-improving goals of LHS. The BD-LHS framework leverages mixed methods approaches to synthesize data across disparate studies, thereby enriching healthcare research and practice. By facilitating a dynamic, iterative exchange between practice, data, and knowledge, BD-LHS aims to enhance the development and implementation of healthcare interventions with an important focus on interdisciplinary collaboration in health informatics. This interdisciplinary methodology ensures that healthcare interventions are both contextually informed and data-driven, enhancing their efficacy and impact. By addressing the need for an integrative approach to knowledge

discovery within LHS, BD-LHS aligns with the core principles of continuous learning and improvement in healthcare.

1.6 Research Hypotheses & Questions

The research objectives outlined in the Specific Aims are explored and validated through the formulation and examination of research hypotheses and corresponding research questions.

Overall Hypothesis: The integration of qualitative analyses from caregiver experiences with computational analyses of clinical data enhances the understanding of the specific needs of children with high-needs, including ASD, thereby facilitating the design, development, and implementation of more effective and sustainable technology-based interventions.

Aim 1: Qualitative Study on Caregivers of High-Needs Children

Hypothesis: Caregivers report that children with high-needs, including those with ASD, experience unique social and emotional impacts, which are exacerbated by inadequate access to necessary resources and services.

Research Question: What are the social and emotional impacts on children with high-needs during the COVID-19 pandemic, and what resources and services are needed to support these families effectively?

Aim 2: Characterization of the ASD Population Using Clinical Data

Hypothesis: Specific comorbidity patterns and risk factors for suicidal thoughts and behaviors (STB) can be identified within the ASD population, differing significantly from those in the non-ASD population.

Research Question: How can computational methods be applied to statewide clinical data to characterize the ASD population, identify comorbidity patterns, and uncover risk factors for suicidal thoughts and behaviors?

Aim 3: Synthesis of Qualitative and Computational Findings for Technological Solution Design

Hypothesis: Integrating qualitative insights from caregivers with computational findings from clinical data analysis will reveal needs and support the development of a targeted technological solution for mental health safety.

Research Question: How can the synthesis of qualitative and quantitative research findings inform the development and requirements of a technology-based application aimed at addressing the unique safety needs and providing customized resources for children with high-needs and ASD?

1.7 Specific Aims

Building upon the BD-LHS framework introduced in the preceding sections, this dissertation aims to leverage the BD-LHS's nested approach within the larger LHS paradigm to address critical gaps in healthcare research and practice, particularly for high-needs children and ASD populations. The BD-LHS framework, with its emphasis on synthesizing qualitative research with computational methods through a convergent mixed methods approach, sets the stage for this dissertation's aims. **Figure 1.6** outlines the specific aims for this dissertation. The goal is to analyze the experiences of caregivers for children with high-needs, characterize ASD populations through computational methods, and synthesize these insights to inform the concept for a targeted technological intervention.

Guided by this overarching goal and grounded in the BD-LHS framework, the dissertation is structured around the following specific aims:

Aim 1: Execute an in-depth qualitative study engaging caregivers of high-needs children in the state of Rhode Island, centering on the social and emotional impacts and the required resources and services.

- a. Facilitate focus group discussions with community members who are caregivers of children with high-needs and carry out a CFIR informed content analysis, followed by a thematic analysis to

elucidate key themes pertaining to the social and emotional impact experienced during the COVID-19 pandemic, and identify resource/service needs to support these families.

- b. Perform a thematic analysis specifically targeting caregivers of children diagnosed with ASD to better understand their unique challenges, needs, and required support services.
- c. Synthesize and prioritize recommendations and implementation strategies that emerge from the content and thematic analyses, with the objective of informing responsive and effective support systems for these caregivers and their children.

Aim 2: Define and characterize the ASD population and associated comorbidities using statewide clinical data and computational methods.

- a. Analyze HIE data to quantitatively characterize the diverse population of children with high-needs in Rhode Island, including assessments of population subgroups and healthcare utilization patterns.
- b. Use association rule mining and sequential pattern mining to identify comorbidity patterns within the ASD population, yielding insights into mental health trajectories.
- c. Apply unsupervised clustering techniques to uncover inherent groupings within the data, enabling the delineation of patient subclasses to enhance the characterization of the ASD demographic.
- d. Develop a predictive model to identify risk factors for Suicidal Thoughts and Behaviors (STB) in children with ASD, highlighting distinctions from the non-ASD population to proactively mitigate these vital safety-related outcomes.

Aim 3: Derive insights through the synthesis of qualitative and quantitative research findings to formulate a comprehensive strategy and define essential requirements for the development of a technology-based application, leveraging the consolidated results.

- a. Integrate qualitative and quantitative insights through use of comparison tables and visual joint displays, facilitating a holistic understanding of the data.
- b. Prototype a technological solution informed by the combined research findings, outlining specific recommendations and prerequisites for a future technological application. This app aims to address the unique safety needs and provide customized resources for children with high-needs and ASD¹⁵³.

- c. Craft a detailed implementation strategy or blueprint, drawing upon the targeted implementation science domains and constructs related to intervention and individual considerations, to ensure a tailored approach¹²⁵.

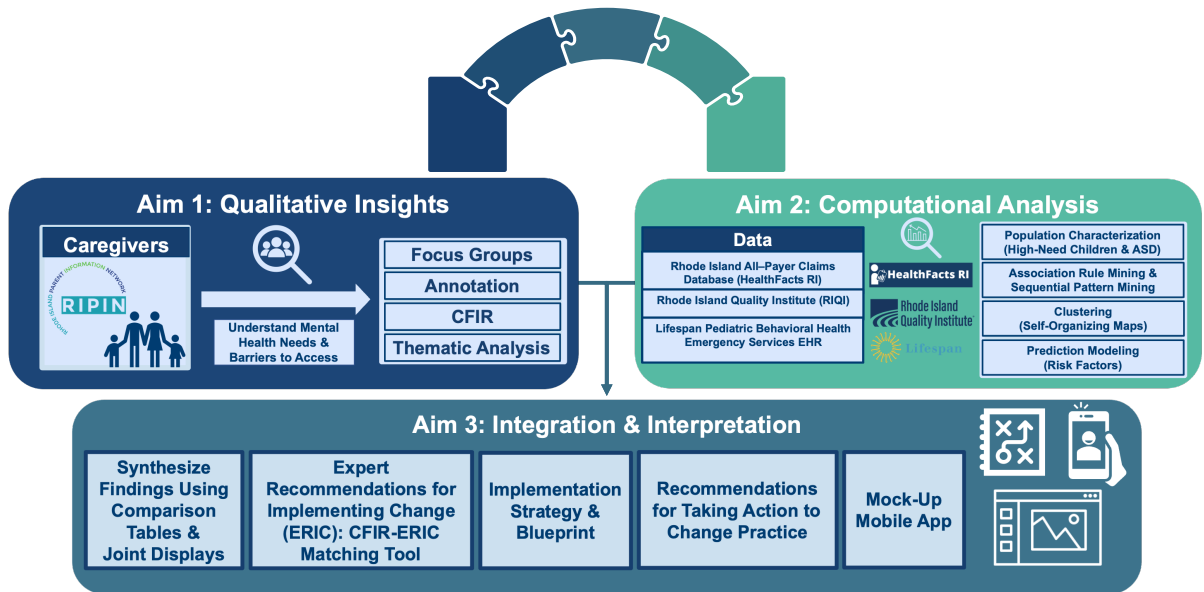


Figure 1.6: Overview of Specific Aims

1.8 Outline of Dissertation

Health informatics approaches offer a powerful means to generate actionable knowledge and design interventions that enhance patient care. This work is anchored in the LHS framework, a dynamic, cyclical model focused on collecting data, generating insights, and implementing interventions that are perpetually optimized to improve healthcare outcomes^{120,121,132,154}. This dissertation introduces BD-LHS as a nested framework situated within the expansive LHS framework. By synergistically integrating qualitative insights with computational methods, the BD-LHS approach aims to gain a more in-depth understanding of healthcare problems. The qualitative findings, by revealing lived experiences and the complex realities of healthcare navigation, provide a critical layer of understanding that quantitative data alone cannot offer. This approach facilitates a deeper understanding of complex health data and accelerates the development and implementation of effective and personalized digital health interventions.

This dissertation is organized into nine chapters, each contributing to the overarching goal of using health informatics approaches to enhance the support and understanding of high-needs children and their caregivers, with a specific focus on ASD.

- **Chapter 1** introduces the dissertation, setting the clinical and informatics contexts. It identifies the knowledge gaps, outlines the theoretical frameworks and approaches, and establishes the specific aims of the dissertation.
- **Chapter 2** presents a scoping review of ASD within the field of health informatics, highlighting how data and technology have been applied to support ASD care and research.
- **Chapter 3** details the execution of **Aim 1**, focusing on a qualitative study with caregivers of high-needs children, exploring the social and emotional challenges, and identifying resource and service needs.
- **Chapter 4 (Aim 2a)** focuses on quantitatively characterizing the high-needs pediatric population through the analysis of statewide data, identifying common conditions, and providing insights into the healthcare requirements of this diverse group.
- **Chapter 4 (Aim 2a), Chapter 5 (Aim 2b), and Chapter 6 (Aim 2c)** use computational methods to characterize the ASD population, examine comorbidities, identify risk factors for suicidal thoughts and behaviors, and analyze clinical data to gain insights into ASD.
- **Chapter 8 (Aim 3)** synthesizes the findings from the qualitative and computational studies to inform the development of a technological solution aimed at addressing the identified needs of high-needs children and their caregivers. It proposes the development of "Pediatric Portal to Access Safety & Services (pediPASS)," a digital safety planning application tailored for children with high-needs and their caregivers. This chapter outlines the app's features, a mockup, and an implementation strategy that considers technical, ethical, and user-experience aspects to ensure the app's functionality, accessibility, and security.

- **Chapter 9** concludes the dissertation, summarizing the key findings, discussing the limitations, and identifying future directions to continue advancing the field of health informatics in supporting ASD and high-needs populations.

Each chapter contributes to the intersection of ASD and health informatics to address the complex needs of these individuals, thereby enhancing the support system for high-needs children and their families.

Chapter 2:

The Intersection of Autism Spectrum Disorder and Health Informatics: A Fifteen-Year Scoping Review

List of Chapter Acronyms

AMIA	= American Medical Informatics Association
ASD	= Autism Spectrum Disorder
CDC	= Centers for Disease Control and Prevention
CDSS	= Clinical Decision support systems
EEG	= electroencephalogram
EHR	= Electronic Health Record
fcMRI	= Functional Connectivity MRI
HIE	= Health Information Exchange
M-CHAT-R	= Modified Checklist for Autism in Toddlers-Revised
MeSH	= Medical Subject Headings
MRI	= Magnetic Resonance Imaging
NLP	= Natural Language Processing

Preface

A version of this chapter is in preparation as a manuscript for submission.

This scoping review provides an examination of the intersection between Autism Spectrum Disorder (ASD) and health informatics, laying the groundwork for a dissertation that seeks to identify and address gaps in research concerning ASD and mental health. Through an analysis of literature spanning from 2009 to 2023, this review elucidates the advancements in health informatics applications for ASD, including diagnostic tools, intervention strategies, and patient technologies. The review focuses on subfields of health informatics with direct implications for ASD research and practice, such as clinical informatics, clinical research informatics, public health informatics, consumer health informatics, imaging informatics, and telehealth. These areas are considered crucial for improving ASD care, diagnosis, intervention strategies, and overall understanding of the disorder. It highlights the evolution of digital tools that facilitate better health outcomes and educational opportunities for individuals with ASD. The review identifies that many of these methods are in their early stages, with limited evaluation and adoption, highlighting the need for

future research to focus on information exchange standards, patient education, and addressing health disparities to enhance patient care outcomes. By highlighting current challenges and limitations within the field, the review provides context and gaps in the research that this dissertation seeks to address. The dissertation aims to delve deeper into these identified gaps, particularly focusing on community and educational needs within the ASD community, to propose targeted solutions that could significantly enhance the quality of care and support available. This foundational work showcases the critical role of health informatics in advancing ASD care and justifies the necessity of further research to optimize and tailor these technological solutions to meet the nuanced needs of the ASD community effectively.

2.1 Introduction

ASD encompasses a group of complex neurodevelopmental conditions characterized by challenges in communication, social interaction, and the presence of repetitive behaviors⁴. The diversity in symptomatology and severity across individuals with ASD necessitates personalized approaches to management and intervention. The past few decades have witnessed a significant uptick in ASD diagnoses, with the Centers for Disease Control and Prevention (CDC) documenting a rise from 1 in 150 children in 2000 to 1 in 36 in 2023⁵. This increase indicates a pressing need for refined early detection, accurate diagnosis, and effective treatment modalities to support the growing population of individuals with ASD and their families¹⁵⁵.

In this context, biomedical informatics emerges as a vital field. It offers transdisciplinary focus on understanding and effectively using data, information, and knowledge to improve patient care and wellness^{156,157}. Spanning from molecular research to population health, this field seeks approaches for translating bench research to bedside application and community health improvement (**Figure 1.2**). Biomedical informatics encompasses subdisciplines like clinical informatics, public health informatics, and translational bioinformatics, employing data science and artificial intelligence techniques such as machine learning and natural language processing^{97,158}. This diverse field offers promising avenues for advancing ASD research, from better understanding the disorder to developing more effective interventions.

Biomedical informatics, a field at the intersection of healthcare and technology, emphasizes the use of advanced techniques for knowledge discovery and process improvement. While computational methods form the bedrock of biomedical informatics, the field's main focus transcends the mere development of computer applications, focusing instead on enhancing patient care. It also explores qualitative dimensions, including how information is used and understood by clinicians, patients, and the broader society^{156,157}. This highlights the field's commitment to ensuring that technological advancements are accessible and meaningful to all stakeholders involved in healthcare.

This scoping review focuses in on the role of health informatics (**Figure 1.2**) in the realm of ASD over the last fifteen years (2009-2023). It assesses the methodologies and applications deployed in screening, diagnosis, and intervention, with a focus on clinical and public health informatics. Despite the potential these technologies hold, many are still in nascent stages, with limited real-world evaluation and adoption. This review identifies key areas for future research, such as enhancing information exchange, developing standards, improving patient education, and addressing health disparities. By tackling these challenges, health informatics can play a role in deepening our understanding of ASD, optimizing resources for patients and caregivers, and ultimately improving health care outcomes for those affected by ASD.

The aim of this review is twofold: (1) to consolidate current knowledge on the application of health informatics in ASD research and (2) to illuminate paths forward for the field. Through an examination of the literature, this review highlights how innovations in data science and technology have contributed to advances in understanding, diagnosing, and treating ASD. Moreover, it underscores the necessity of integrating computational and non-computational approaches to fully harness the potential of health informatics in improving care for individuals with ASD.

2.2 Methods

Search Strategy

This review was conducted as a scoping review to identify and describe key research topics at the intersection of ASD and various domains of informatics. A scoping review systematically and iteratively synthesizes current and emerging literature on a topic^{159–162}. Its primary goals are to chart the scope, diversity, and characteristics of this literature and to identify any gaps in knowledge. The scoping review approach allows for a broader exploration of the topic without the specific focus on synthesizing outcome measures.

The literature search strategy was comprehensive to ensure a wide coverage of relevant studies. PubMed was the primary database used, employing Medical Subject Headings (MeSH) to refine the search. Key terms included “Autism Spectrum Disorder” in conjunction with “Informatics” which represents various branches of informatics including but not limited to: “Computational Biology,” “Consumer Health Informatics,” “Medical Informatics,” “Nursing Informatics,” “Dental Informatics,” and “Public Health Informatics,” among others. Another key database, Embase, was searched using terms such as “autism” and “medical informatics” to capture relevant studies. To encompass a broader range of grey literature and non-peer-reviewed sources, a Google Scholar search was also conducted. This search included terms like “autism,” “biomedical informatics,” “computer applications,” “clinical decision support,” “telemedicine,” and “public health informatics.”

Inclusion & Exclusion Criteria

The inclusion criteria for this scoping review were intentionally broad to capture the wide range of studies intersecting ASD and informatics. This approach allowed for the identification and thematic analysis of key areas in addition to gaps in the research. The review process included identifying relevant studies, selecting studies based on inclusion criteria, reviewing the inclusion papers, creating a data extraction table, summarizing, and reporting the results. The goal of this scoping review was to identify and summarize the

findings of existing research and highlight areas where further study is needed, thus providing an overview of the current landscape of research at the nexus of ASD and informatics.

To focus the scope of this dissertation on the most relevant subfields of biomedical informatics for ASD, this review explicitly excludes translational bioinformatics from the analysis. The decision to omit translational bioinformatics stems from its primary focus on the molecular and genomic aspects of healthcare, which, while invaluable in many areas of medical research, diverges from the central topics of interest in this dissertation. Translational bioinformatics, a vast and specialized field, emphasizes the application of informatics techniques to molecular biology, genetics, and genomics. Its primary aim is to enhance the understanding of biological processes and diseases at the molecular level to facilitate the development of targeted therapies and personalized medicine. Although translational bioinformatics holds significant potential for advancing medical science and has applications in various disorders, including neurodevelopmental conditions, its direct relevance to the practical, clinical, and public health aspects of ASD is limited within the context of this dissertation. The complexity and scope of translational bioinformatics could dilute the focus on applied health informatics strategies that are more immediately pertinent to improving ASD care, diagnosis, and intervention strategies.

Therefore, this dissertation centers on subfields of *health informatics* that offer direct implications for ASD research and practice¹⁶³. *Clinical informatics* focuses on the use of information technology in healthcare delivery, emphasizing electronic health records (EHRs), clinical decision support systems, and information management to improve patient care specifically for ASD^{97,157,164,165}. **Public health informatics** is defined as the field that uses informatics techniques and technologies within the sphere of public health. This includes activities like monitoring, prevention, emergency preparedness, and promoting health to deepen our understanding of ASD trends and their effects across populations¹⁶⁶. **Consumer health informatics** explores how health information is communicated to and used by patients and caregivers, particularly in the context of ASD, to support self-management, decision-making, and patient-centered care¹⁰⁸. **Telehealth** involves using technology to provide health care, share medical information, and educate patients remotely.

It aims to enhance support and increase health service accessibility for individuals with Autism Spectrum Disorder (ASD) and their families¹⁶⁷. **Clinical research informatics** focuses on enhancing the efficiency and effectiveness of clinical research by employing informatics methods and tools. In the context of ASD, clinical research informatics can revolutionize the way clinical trials are designed, data are collected, and analyses are performed¹⁰⁴. **Imaging informatics** enhances ASD research by leveraging advanced imaging technologies and computational methods to analyze brain structures and functions, offering critical insights into the neural mechanisms underlying ASD and supporting the development of targeted interventions^{106,168}. By concentrating on these areas, the dissertation aims to provide a review of the current and potential contributions of health informatics to ASD research and practice. This focused approach allows for a deep dive into the ways in which informatics can enhance understanding, diagnosis, intervention, and overall care for individuals with ASD, thereby offering tangible benefits and improvements in their lives and the healthcare systems that support them.

Table 2.1 presents an outline of the inclusion and exclusion criteria established through systematic search strategies. These criteria have been defined to ensure the selection of studies that are most relevant to the scope of the research on ASD and its intersection with informatics. The table delineates the specific characteristics that qualify research for inclusion, such as population focus, conceptual relevance, source type, and publication window. Simultaneously, it specifies the conditions under which studies are deemed not applicable for the review, guiding the systematic exclusion of unrelated or out-of-scope literature. This methodological rigor enhances the precision and relevance of the literature mapping, facilitating a focused and insightful exploration of the field.

Table 2.1: Inclusion and Exclusion Criteria for Literature Selection

Criteria Type	Description
Inclusion Criteria	Population: Studies involving individuals diagnosed with ASD, regardless of age, gender, or ethnicity. Health Informatics Domains: clinical informatics, clinical research informatics, consumer health informatics, imaging informatics, public health informatics, telehealth Concept: Research that investigates the application of informatics in ASD, including clinical informatics, public health informatics, and translational bioinformatics. Type of Sources: Peer-reviewed research articles, conference proceedings, and grey literature (e.g., theses, dissertations, technical reports) published from 2009 to 2023. Language: Articles published in English.
Exclusion Criteria	Population: Studies not specifically addressing ASD (e.g., studies on broad developmental disorders without specific focus on ASD). Biomedical Informatics Domains: Translational Bioinformatics Concept: Research that does not use informatics tools or methodologies in the context of ASD. Type of Sources: Non-peer-reviewed articles, opinion pieces, editorials, and literature reviews. Publication Date: Studies published before 2009 or after 2023. Language: Articles not published in English.

Selection Criteria

Publications were evaluated based on their central investigation of ASD and application of health informatics. Selection favored studies articulating computer-based innovations aiding ASD clinical care. Criteria for inclusion and exclusion, as delineated in **Table 2.1**, derived from structured searches. Articles underwent analysis against biomedical informatics subfields based on the application areas or subfields as defined by the American Medical Informatics Association (AMIA) along with topics discussed in the text *Biomedical Informatics: Computer Applications in Health Care and Biomedicine* (E. Shortliffe & J. Cimino, 2013)^{96,164}. Categorization encompassed six primary informatics sub-disciplines as described

above: (1) clinical informatics, (2) clinical research informatics, (3) consumer health informatics, (4) imaging informatics, (5) public health informatics, and (6) telehealth.

Data Extraction

The data extraction methodology was developed to provide a thorough review the literature on the use of health informatics in ASD research. A pre-defined charting form served as the backbone of this process, capturing critical information such as study author, year of publication, geographical location, key informatics methodologies, key findings, and implications for practice. This structured approach organized and synthesized data across the diverse array of studies included in this scoping review. To deepen the analysis, a thematic analysis was integral to the review process, enabling the identification of seven key research objectives that emerged as recurrent themes throughout the literature. This thematic analysis was instrumental in mapping the current state of the field and highlighted the interdisciplinary and multifaceted nature of research efforts in ASD and informatics. Each included study was carefully analyzed and assigned to one or more of these research objectives, based on its primary focus and contributions. This categorization facilitated a targeted synthesis of the literature, allowing for a detailed exploration of each theme and its relevance to advancing ASD research and practice.

In addition to categorizing studies by research objectives, each study was also classified according to one or more informatics subfields. This dual-layered categorization highlights the diverse informatics approaches being employed to address the identified research objectives and highlighted the collaborative efforts across various domains of informatics to advance ASD research. The alignment of studies with specific research objectives and informatics subfields was documented in the data extraction table. This table captures essential study details reflected the thematic analysis outcomes, providing a snapshot of the research landscape. The synthesis of extracted data, guided by the thematic analysis, involved creating a narrative summary that articulated the methodologies, findings, and identified gaps within each informatics subfield. This synthesis aimed to provide a holistic overview of the field's current state, emphasizing how different informatics subfields contribute uniquely to addressing the challenges and opportunities in ASD

research. By integrating the research objective themes into the data extraction and synthesis processes, this enhanced methodological approach ensures a rich, detailed, and organized exploration of the literature, paving the way for identifying important directions for future research and intervention development.

2.3 Results

Article Selection

The initial search for this scoping review was conducted with a broad temporal scope of the past thirty years (starting from 1993) to capture a historical perspective capturing a total of 1,102 articles. A thorough analysis of the literature led to a strategic refinement of the inclusion criteria, focusing on articles published within the last fifteen years, from 2009 to 2023. This refinement was informed by the recognition that most of the pertinent research, or roughly 88%, has been conducted within this timeframe. As illustrated in **Figure 2.1**, a significant proportion of the articles retrieved from PubMed, Embase, and Google Scholar fall within this period, highlighting a concentrated burst of activity and advancements in the field. This temporal focus ensures the review's relevance and alignment with the latest developments and insights in this area of research.

Publications Per Year (ASD & Informatics Initial Search)

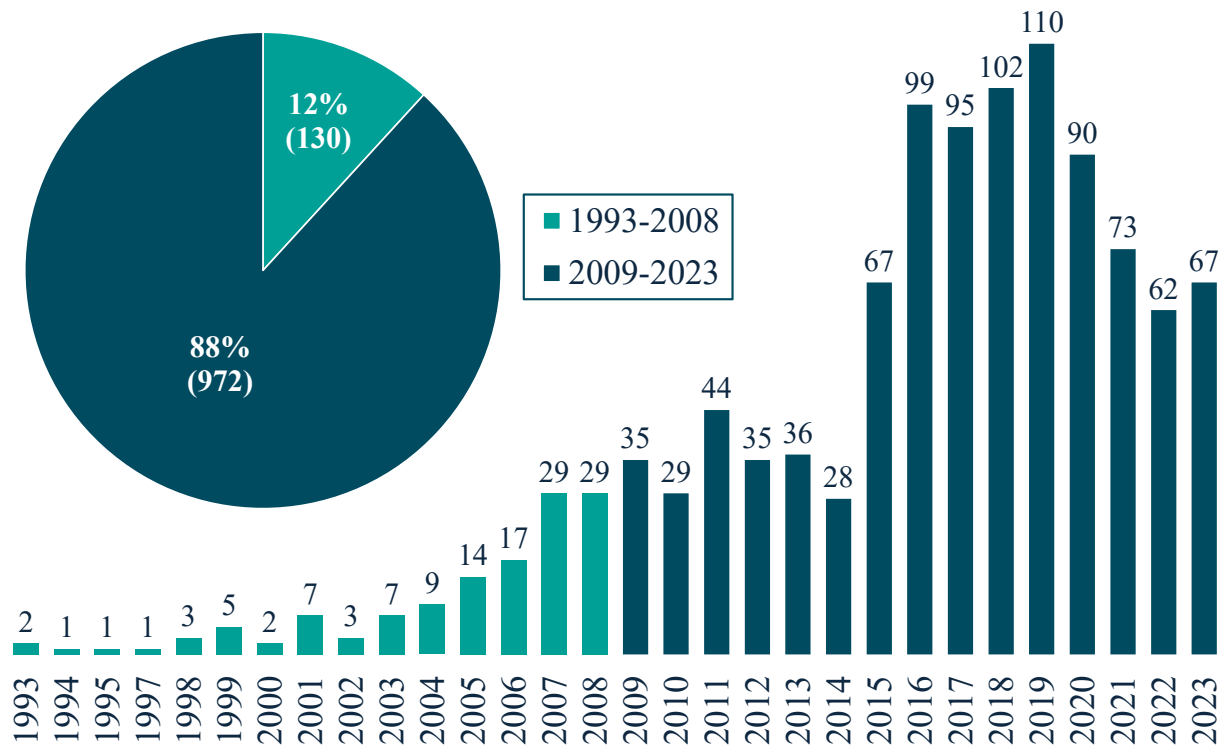


Figure 2.1: Distribution of Search Results from 1993 to 2023

The comprehensive search strategy and selection process applied to PubMed, Embase, and Google Scholar databases yielded a collection of research that reflects the multifaceted intersection of ASD and the field of health informatics. An initial pool of 972 articles was identified and examined to align with the scoping review's inclusion criteria, which led to a detailed examination of 378 articles at the abstract level. This refined process led to full-text review and inclusion of **140** articles, chosen to represent a diverse array of research across the various subdisciplines of health informatics. **Appendix A** includes a table and overview of the articles selected for inclusion, showcasing the range of research relevant to biomedical informatics in the realm of ASD.

To provide a structured overview of the subfields within health informatics represented in the scoping review, **Table 2.2** was constructed. This table categorizes the 140 selected articles by informatics subfield, demonstrating the frequencies and thus the relative emphasis placed on each domain within the realm of ASD research. **Figure 2.2** complements this tabular data by graphically depicting the spread of articles across the informatics subfields, offering an intuitive grasp of the scope and focus areas within the field.

The deliberate exclusion of translational bioinformatics from this review narrows the focus to those subfields most pertinent to the direct application in clinical, public health, and patient-centered contexts. The distribution as presented in **Table 2.2** and **Figure 2.2** reflects the current state of the field, highlighting the prominent role of clinical informatics while also acknowledging the contributions of less represented yet vital areas such as telehealth and public health informatics. This curated selection of articles, further detailed in Appendix A, showcases the dynamic and evolving landscape of ASD research in biomedical informatics, underlining the depth and interdisciplinarity that characterize this critical area of study.

Table 2.2: Frequency of Articles by Biomedical Informatics Subfield in ASD Research

Informatics Subfield	Frequency
Clinical Informatics	64
Clinical Research Informatics	29
Consumer Health Informatics	19
Imaging Informatics	15
Public Health Informatics	12
Telehealth	8
Translational Bioinformatics	<i>Excluded</i>

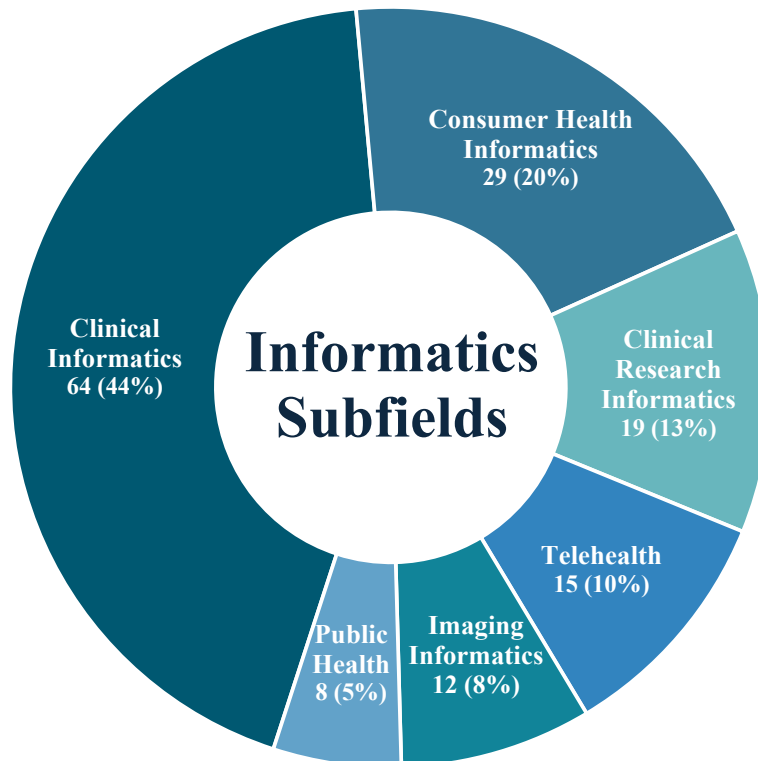


Figure 2.2: Distribution of ASD Informatics Research Across Health Informatics Subfields

Research Objectives

The thematic analysis conducted as part of this scoping review identified seven research objectives that collectively encapsulate the breadth and depth of the intersection between ASD and health informatics. These objectives reflect the diverse research directions and priorities within the field, highlighting the key areas where informatics has the potential to significantly impact the understanding, diagnosis, intervention, and management of ASD. Below is an introduction to each of the seven research objectives identified:

1. **Case Identification/Database Infrastructure:** Focuses on the development and enhancement of informatics-based systems and databases for the accurate identification and categorization of ASD cases. It underscores the importance of data infrastructure in facilitating research, enhancing diagnostic precision, and supporting epidemiological studies.
2. **Discover New Knowledge:** Emphasizes the role of informatics in generating insights into the etiology, progression, and heterogeneity of ASD. This involves leveraging data analytics, machine learning, and other computational methods to unearth patterns and correlations within large datasets that could lead to breakthroughs in understanding ASD.
3. **Early Detection: Diagnostics/Screening Tool:** Highlights the application of informatics tools and methodologies in developing and refining early detection and diagnostic screening tools for ASD. This objective is critical for ensuring timely intervention and support for individuals with ASD, potentially mitigating the impact of the disorder on long-term outcomes.
4. **Interoperability/Sharing Information/Standards:** Addresses the necessity of establishing and adhering to standards for data interoperability and sharing across different systems and platforms. This ensures that data collected from various sources can be integrated and used effectively, enhancing collaboration and facilitating more research efforts.
5. **Intervention/Therapy Development:** Focuses on the use of informatics in the design, development, and evaluation of interventions and therapies for ASD. This includes the creation of

technology-based therapeutic tools, as well as the analysis of intervention outcomes and efficacy using informatics approaches.

6. **Reduce Health Disparities:** Aims at leveraging informatics to identify and address health disparities within the ASD community. This involves analyzing data to understand how various social, economic, and geographic factors influence the access to and quality of ASD care and services, with the goal of promoting equity in health outcomes.
7. **Patient Education/Patient Engagement:** Centers on the use of informatics to enhance patient education and engagement. This objective recognizes the importance of empowering individuals with ASD and their families with information and tools to actively participate in care and decision-making processes.

These research objectives serve as the foundation for the review's analysis, guiding the exploration of how informatics is being used to advance ASD research and care. The identification of these objectives facilitates a structured examination of the existing literature and illuminates areas where further research and development are urgently needed. By addressing these objectives, the field of health informatics holds the promise of making significant contributions to improving the lives of individuals with ASD and their families.

Table 2.3 and **Figure 2.3** present the distribution of research objectives identified in the 140 articles included in the scoping review, which cover a fifteen-year period of literature on ASD and informatics research. **Table 2.3** categorizes the articles based on the frequency of each research objective, providing a quantifiable overview of the areas of focus within the intersection of ASD and informatics research over the past fifteen years. Complementing this, **Figure 2.3** offers a visual representation of the distribution of these objectives, illustrating the proportion of studies dedicated to each area. This visualization facilitates an understanding of the research landscape, revealing the extent and focus for each objective within the field potentially reflecting the evolving priorities and advancements in ASD informatics research.

Table 2.3: *Distribution of Identified Research Objectives in ASD Informatics Literature*

Research Objective	Frequency
Case Identification/Database Infrastructure	13
Discover New Knowledge	57
Early Detection: Diagnostics/Screening Tool	36
Interoperability/Sharing Information/Standards	6
Intervention/Therapy Development	26
Reduce Health Disparities	12
Patient Education/Patient Engagement	16

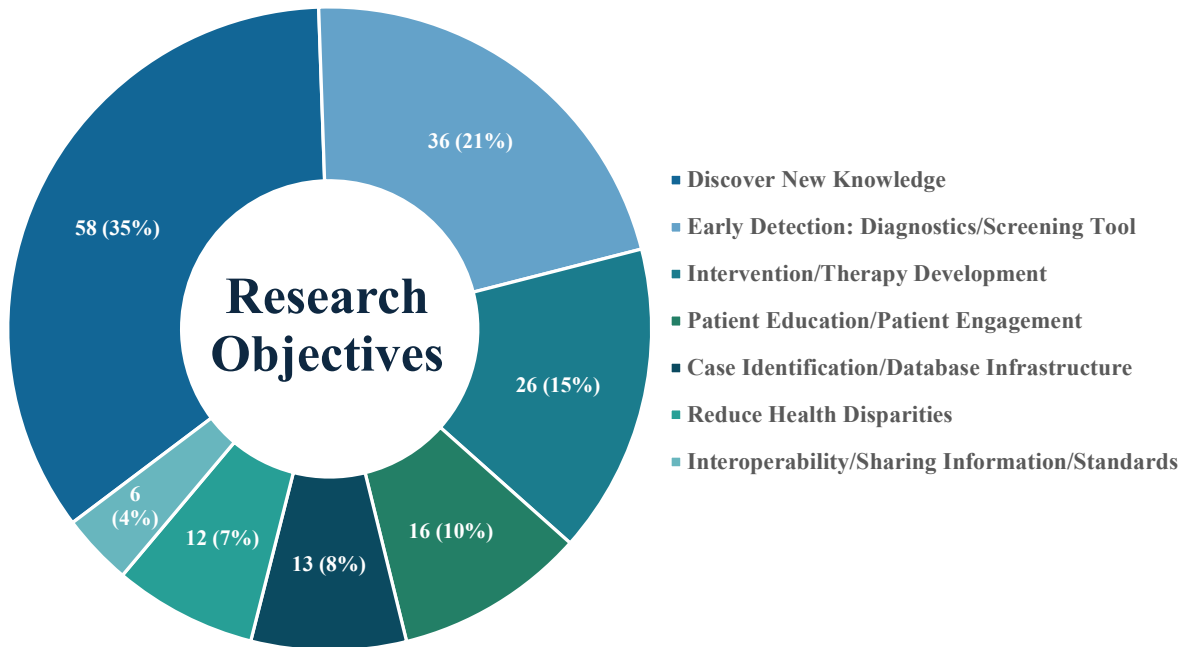


Figure 2.3: *Representation of Research Objectives in ASD Informatics Studies*

Figure 2.4 provides a detailed visualization of the alignment between the various informatics subfields and the seven identified research objectives within the scope of ASD research. This figure illustrates a matrix that cross-references each informatics subfield with the frequency of research objectives addressed within that domain. Clinical Informatics shows a substantial focus on 'Discover New Knowledge', which is the most frequent objective within this subfield, followed by 'Early Detection: Diagnostics/Screening Tool' and 'Intervention/Therapy Development'. This indicates a strong emphasis on using clinical data to further understand ASD and develop diagnostic and therapeutic tools. Clinical Research Informatics is primarily associated with the objective of 'Discover New Knowledge', reflecting its critical role in advancing research that contributes new insights into ASD. Consumer Health Informatics exhibits a balanced focus, with notable attention given to 'Discover New Knowledge' and 'Early Detection: Diagnostics/Screening Tool', emphasizing the importance of consumer-focused technologies in both understanding and identifying ASD. Imaging Informatics predominantly addresses 'Discover New Knowledge' and 'Early Detection: Diagnostics/Screening Tool', highlighting the use of imaging technologies to explore neural correlates of ASD and develop screening methodologies. Public Health Informatics, while having a relatively lower overall representation, shows a diverse engagement across objectives, particularly in 'Reduce Health Disparities' and 'Patient Education/Patient Engagement', underlining the role of informatics in addressing broader public health challenges related to ASD. Telehealth is seen engaging primarily with 'Patient Education/Patient Engagement', suggesting a focus on using telecommunication technologies to enhance patient involvement and education in ASD care. The distributions depicted in **Figure 2.4** highlights the interdisciplinary approaches within health informatics in addressing ASD, with varied focus areas aligning with specific research objectives. This matrix serves to highlight both the convergence and divergence in research efforts across different informatics domains, offering a view of how informatics tools and methodologies are being used to advance the field of ASD research.

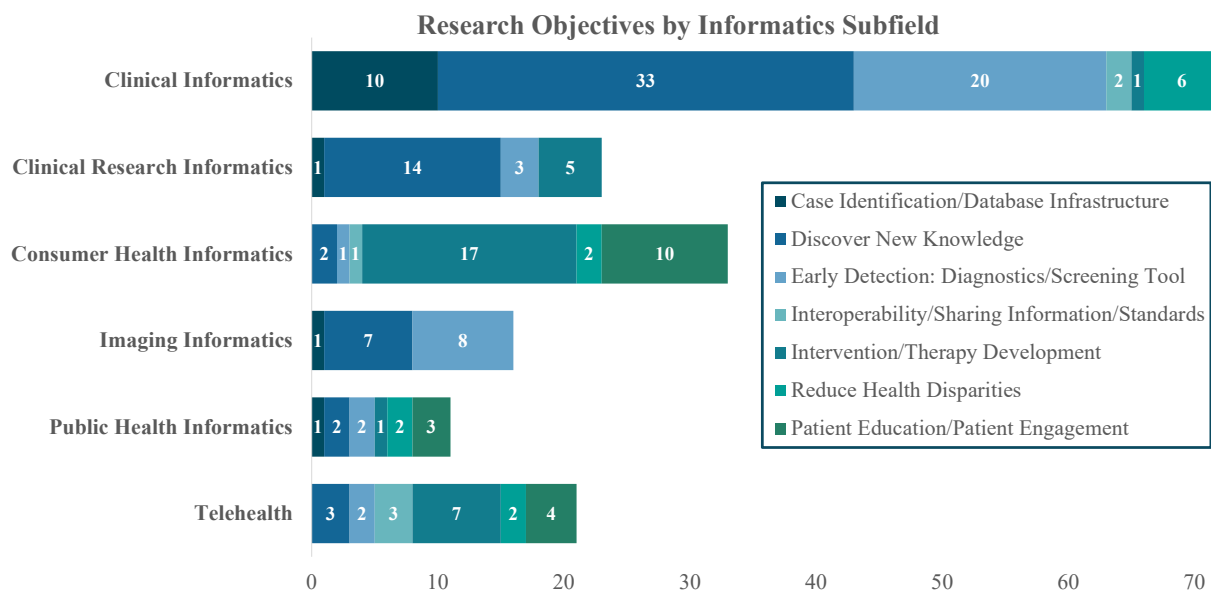


Figure 2.4: Research Objective Frequencies Per Informatics Domains

2.4 Discussion

This scoping review examined the contributions of health informatics to ASD research, uncovering the myriad ways in which data and technology, when harnessed effectively, can offer profound insights and foster enhanced care strategies. Given the complexity and varied presentations of ASD, the imperative for early detection and timely intervention is clear—goals that are directly supported by the tools and methodologies of health informatics. This interdisciplinary field has the potential to revolutionize the diagnostic landscape for ASD, providing faster and more accurate diagnostic tools that are essential for effective treatment planning. Beyond diagnostics, health informatics paves the way for the innovation of interventions and the refinement of existing therapeutic techniques, potentially improving outcomes for individuals with ASD.

This review synthesized the contributions of 140 studies which brought to light a diversity of studies spanning several key subdisciplines within health informatics. These encompass clinical informatics, clinical research informatics, consumer health informatics, public health informatics, and imaging

informatics, each contributing unique insights and approaches to ASD research. From data extraction to the application of machine learning and natural language processing, and from genomic research to the development of assistive technologies, the methodologies employed are as varied as they are impactful. In the subsequent sections, the specific contributions of each informatics subfield to ASD research are described, drawing out the different research objectives and ways in which they leverage technology to advance understanding and management of the disorder. This analysis highlights the progress and sets the stage for future explorations that may further transform the landscape of ASD diagnosis, treatment, and care.

Research Objectives

The literature spanning fifteen years in ASD and informatics research elucidate patterns in common research objectives and goals. The top theme to “Discover New Knowledge” is identified as the primary objective in 57 articles (35%), targeting the broad aim of advancing our understanding of the unknown aspects of ASD. This is followed by 'Early Detection: Diagnostics/Screening Tool', which was the focus of 36 studies (21%). Early intervention is vital for ASD treatment, so this made sense as a top research objective to enhance the diagnostic and screening tools for the disorder. The objective of 'Intervention/Therapy Development' was another common objective, with 26 articles (15% of the total) illustrating the interest in the transformative potential of informatics for therapy enhancement in ASD. The objectives of 'Patient Education/Patient Engagement' and 'Case Identification/Database Infrastructure' had moderate coverage, with 16 (10%) and 13 (8%) articles respectively, highlighting the field's increasing investment in patient-centric informatics applications and the foundational data architectures required for effective ASD management. Furthermore, the objective to 'Reduce Health Disparities', represented in 12 articles (7%), informatics approaches can be used to improve equity in the delivery of ASD care and services. The least represented yet vital objective, 'Interoperability/Sharing Information/Standards', seen in 6 articles (4%), points to the essential need for data integration across diverse informatics systems to support cohesive ASD research and practice.

This review, through its categorization of research priorities articulates the multifaceted nature of informatics applications in ASD research and provides a roadmap for future scholarly endeavors. It pinpoints both the well-trodden paths and the less chartered terrains, offering insights into potential areas ripe for development and exploration, ultimately guiding the next wave of innovation in the nexus of ASD and informatics.

Clinical Informatics

Clinical informatics contributes to advancing our understanding of ASD, with a focus on early detection, diagnosis, and management. Clinical informatics plays a central role in enhancing patient care and facilitating healthcare delivery through the effective management of information and application of information technology¹⁶⁴. Its primary domains encompass health information systems, EHRs, clinical decision support systems, data mining, pattern recognition, data standards, phenotyping, care process improvement, and change management¹⁶⁵.

Data extracted from EHRS can aid in diagnosing ASD. This streamlines the screening and diagnostic procedures, supports clinical decision-making, and uncovers new correlations to deepen our understanding of ASD and guide future research endeavors. This scoping review highlights the prevalent use of EHRs in research, focusing on harnessing data from patient cohorts to unravel ASD's complexities, facilitate diagnosis, and identifying comorbidities. EHRs provide consolidated patient information, clinician order entry, clinical decision support, medical knowledge access, and communication and reporting systems⁹⁶. The recent literature highlights a trend toward employing advanced machine learning techniques to improve the accuracy and efficiency of ASD detection. For instance, some studies leverage machine learning algorithms on home videos and mobile-based applications to screen for ASD, suggesting a move towards more accessible and remote diagnostic tools^{169,170}. These methods demonstrate high true positive rates and clinically acceptable accuracy, underscoring the utility of informatics in early detection efforts.

The publications explore the application of data mining and machine learning to leverage EHR data, employing ICD codes and other data sources to identify ASD cases. These methodologies, including health informatics, NLP, and machine learning methodologies, facilitate pattern identification among patient cohorts. These approaches can also uncover unknown patterns and comorbidities related to ASD^{7,10,171–185}. Some studies have used online databases, like the Interactive Autism Network (IAN), for analyzing anxiety and mood disorders within ASD populations¹⁸⁶. The review reveals varied data extraction and mining techniques across studies, with many emphasizing the significance of NLP¹⁸⁷. NLP is crucial for extracting and representing information from unstructured clinical notes, thereby overcoming the limitations and errors associated with traditional diagnostic coding systems like ICD-9-CM or ICD-10-CM codes⁹⁶. Machine learning combined with NLP has also been used to extract information from EHRs enhancing case identification and phenotyping. Some studies developed machine learning models that improve diagnostic processes and help in understanding the underlying complexities of ASD, including comorbid conditions^{188,189}. Others used condition groupings to analyze and characterize co-occurring medical conditions, illuminating the multifaceted medical burden experienced by individuals with ASD¹⁹⁰. Machine learning and algorithmic approaches to EHR data analysis can expedite the discovery of phenotypes, crucial for a condition as complex and multifaceted as ASD^{191–197}. Ontology creation, aimed at comparing ASD assessment instruments and linking genotypic and phenotypic information across various databases, serves as another method for enhancing ASD research and diagnosis^{198–200}. In the realm of phenotyping, research has shifted towards the identification of ASD subtypes and their treatment responses. Identifying phenotypes and characteristics across patient populations is a strategy for advancing understanding of diseases like ASD. This is exemplified in the work where machine learning techniques were used to identify behavioral phenotypes, providing a pathway towards personalized interventions²⁰¹. Additionally, network analysis has been employed to explore disease comorbidity patterns, offering new insights into potential diagnostic and therapeutic strategies²⁰².

Early detection of ASD is paramount for the efficacy of interventions^{203–206}. The review notes advancements in this area, such as the transformation of unstructured and semi-structured data from handwritten medical forms into digital formats using NLP frameworks and machine learning techniques. This innovation significantly accelerates the ASD diagnostic process²⁰⁷. Additionally, the development and implementation of digital screening tools like the Modified Checklist for Autism in Toddlers-Revised with Follow-up (M-CHAT-R/F) have shown promise in enhancing early ASD detection through improved outcomes and documentation accuracy within EHR systems^{208–211}. The integration of clinical informatics into ASD research has opened doors to diagnostic frameworks²¹². For example, Andrade et al. evaluated a hybrid methodology combining machine learning with verbal decision analysis, refining diagnostic protocols and decision-making processes in ASD diagnoses²¹³. Heyl et al. tackled data quality issues, revealing that inconsistencies in healthcare datasets could impact the accuracy of ASD-related healthcare research and patient outcomes²¹⁴. Some studies extended beyond ASD diagnosis, such as showcasing the Interactive Trauma Scale (ITS) as a promising intervention and screening tool. This web-based touchscreen measure aids in the sensitive assessment of trauma exposure in children with ASD but also highlights the broader applicability of informatics tools in addressing complex clinical needs beyond initial diagnostics²¹⁵.

Clinical decision support systems (CDSS) have also seen applications in the context of ASD. Studies have implemented EHR modifications and electronic supports to enhance autism screening and referral rates in primary care settings²¹⁶. These interventions have led to significant improvements, suggesting that technology can play a role in streamlining the diagnostic journey for ASD. CDSS are designed to assist clinicians in the ASD diagnostic process and improve outcomes based on evidence-based guidelines. Examples include the use of wearable technology for detecting stereotypical motor movements and CDS modules to ensure adherence to clinical guidelines, although their impact on physician attitudes or knowledge remains inconclusive^{64,115,194,217–223}.

A few recent studies in the past five years have used healthcare cost and other data from EHRs and hospital systems with a focus on reducing health disparities in ASD care. One study highlighted the increased

likelihood of hospitalizations for self-injurious behavior in adults with ASD, pointing to longer hospital stays and higher associated costs, underscoring the urgent need for targeted interventions to mitigate these outcomes and reduce healthcare disparities²²⁴. These studies emphasize the critical role of clinical informatics in identifying and addressing health disparities within the ASD population. By leveraging data from EHRs and employing models like ECHO, research is paving the way for more equitable healthcare delivery, emphasizing the need for targeted interventions, and support systems to address the unique challenges faced by individuals with ASD and their families^{225–227}. Addressing health disparities and involving families in ASD research marks a positive shift towards inclusivity and equity. Historically, these areas were less emphasized, indicating that current efforts are a step in the right direction. However, there's a need for continued focus to ensure support and equitable care for the ASD community.

Throughout the recent literature, it is evident that clinical informatics is transforming the way we approach ASD diagnosis and treatment enhancing our understanding of the disorder's broad spectrum. By leveraging big data, machine learning, and NLP, researchers are paving the way for more effective, efficient, and personalized care for individuals with ASD. This examination highlights the potential of clinical informatics in advancing ASD diagnosis, treatment, and research, emphasizing the importance of continuous innovation and integration of technology in healthcare.

Clinical Research Informatics

Clinical research informatics applies informatics tools and methodologies to uncover new insights into diseases and health, encompassing a broad spectrum from basic research through clinical trials to community or population-based studies^{104,164}. In the realm of ASD, clinical research informatics advances research, facilitating a range of clinical trials and studies aimed at exploring ASD's wide range of presentations and complexities.

A significant area of focus within this domain is the exploration of ASD's progression and its genetic underpinnings. Various studies have engaged patients in research to examine the developmental trajectory

of ASD and identify genetic factors that may contribute to the disorder. For instance, one study used a random forest model to analyze data from seven tasks, successfully identifying differentiating subgroups of individuals with ASD. These subgroups reveal potential variations in ASD's etiology, offering valuable insights that could refine diagnostic criteria and inform the development of tailored treatment strategies for patient profiles^{228,229}. Recent research has also delved into the gut microbiota profiles of individuals with ASD, spurred by findings that suggest notable differences in the gut microbiomes of children with ASD compared to their neurotypical peers²³⁰. This line of inquiry holds promise for elucidating the relationship between gut health and ASD, potentially leading to identification of diagnostic markers or therapeutic approaches. Other studies encompass a broader spectrum methodologies, employing a variety of informatics methods to advance our understanding of ASD and improve diagnostic and intervention strategies^{231–233}. Automated and computational methods, such as the use of automated objective measures²³⁴, Bluetooth low energy (BLE) beacon-based algorithms²³⁵, and computer vision analysis²³⁶ have shown promise in enhancing the quantification of social communication and behavior in community settings and the home environment. These technologies offer new insights into ASD, allowing for the objective measurement of social behavior and communication opportunities, thus overcoming limitations of traditional observational methods. Furthermore, mobile and app-based technologies demonstrate the utility of digital tools in both research and intervention^{237–240}. These approaches facilitate the exploration of social engagement indicators and the delivery of interventions, emphasizing the value of telehealth and mobile apps in extending the reach and effectiveness of ASD therapies and assessments.

Statistical and machine learning techniques can help identify new knowledge and potential diagnostic markers for ASD. Studies used these methods to explore factors influencing ASD severity and to develop high-performance diagnostic tools^{241,242}. The effectiveness of machine learning and eye-tracking in diagnosing ASD underscores the potential of integrating informatics tools with clinical research to improve early detection and intervention strategies^{243–245}. The investigation of sensor-based biomarkers has emerged as a groundbreaking area of research within clinical research informatics. Studies employing quantitative

measures of symptoms—such as facial expressions, body language, electroencephalogram (EEG) patterns, eye tracking, and other bio-sensory data—aim to identify common pathophysiological traits among individuals with ASD. The insights gained from this research are expected to enhance the ability to characterize ASD more accurately, evaluate clinical outcomes, and guide more effective therapeutic techniques and interventions²⁴⁶.

The collective findings from these studies underscore the essential role of clinical research informatics in advancing ASD research. By leveraging advanced informatics applications, researchers can dissect the multifaceted nature of ASD, from genetic and behavioral profiles to physiological markers, contributing to the development of more effective diagnostic, monitoring, and intervention strategies. This approach deepens our understanding of ASD and paves the way for more personalized and effective diagnostic and treatment modalities.

Consumer Health Informatics

Consumer health informatics is a subfield of health informatics that links patients and healthcare providers through technology, enhancing access to health information and improving healthcare outcomes¹⁰⁸. Effective management of health conditions necessitates collaboration among clinicians, inter-professional teams, patients, family members, and the broader society⁹⁶. ASD studies have highlighted the role of assistive technologies and devices in therapy and interventions, aiding in the identification and management of ASD characteristics, such as stereotypical motor movements. These technologies contribute to enhancing personal health records and EHRs, facilitating a deeper understanding of patient symptoms and tailoring interventions accordingly. Additionally, new technologies aim to improve ASD patient behaviors and overall outcomes^{247–251}.

Several studies have explored the use of technology to enhance therapeutic interventions for individuals with ASD^{252–256}. For instance, the use of Robot Enhanced Therapy (RET) was supported by the DREAM Dataset, which provided a foundation for data-driven studies involving children with ASD and robots²³¹.

Similarly, the development and testing of a multi-sensor-based hardware prototype showed significant reduction in hyperactive states in individuals with ASD²⁵⁷, and the evaluation of a mobile app (ASDetect) highlighted its potential in improving early autism detection²⁵⁸. Studies have explored the use of technology to foster social skills and communication. One study compared Mixed Reality experiences with traditional interventions, finding no significant difference in anxiety levels, suggesting MR's potential in social skills development²⁵⁹. Additionally, the feasibility study of a mobile game platform, GuessWhat, indicated significant improvements in social responsiveness and adaptive behavior scales, supporting its therapeutic viability²⁶⁰. Insights from parental interviews on media content preferences²⁶¹ and the development of a public transport planning tool²⁶² illustrate the importance of developing content and tools that consider the unique needs and preferences of individuals with ASD. Technology-based interventions have also shown promise in supporting educational and behavioral outcomes. The I-Connect Self-Monitoring Intervention was found to improve on-task and task completion behaviors in adolescents with ASD²⁶³, and a study on the TOBY iPad app highlighted its variability in effectiveness, underscoring the need for personalized approaches²⁶⁴.

Moreover, studies examining the connection between EHRs and the experiences of families with ASD children highlight the impact on service access, therapy, and intervention. Despite the benefits of EHRs and patient portals for enhancing communication, challenges remain, such as limited patient portal registration²⁶⁵. Research also delves into how health records can influence disparities in ASD diagnosis and access to services²⁶⁶, offering insights into the potential of EHRs to improve care and reduce health disparities^{267,268}. A significant aspect of consumer health informatics involves how patients interact with and comprehend information about their health. Tools like the Autism Management Platform (AMP) exemplify this, offering a web-based interface and mobile application for data and multimedia integration between clinicians and parents, thus enhancing communication and aiding in ASD diagnosis and treatment²⁶⁹. Patient engagement and education are further underscored by research into information preferences among parents of children with ASD. This emphasizes the importance of health informatics in

navigating the vast amount of information available to consumers and improving patient and parent education^{270,271}.

The use of wearable and mobile technology for real-time monitoring and intervention has emerged as a significant theme. One study focused on recognizing stress and anxiety through wearables and machine learning demonstrated the feasibility of using such data for real-time intervention²⁷². Another study also emphasized the value of user-centered design in developing wearable applications to support daily activities for children with ASD²⁷³.

These studies showcase the ways in which consumer health informatics can support individuals with ASD and their families. The integration of technology into therapeutic, educational, and daily living interventions offers promising avenues for enhancing the quality of life for individuals with ASD. However, it also illuminates the importance of individualized approaches and the need for further research to optimize the design, implementation, and evaluation of these technologies. Future research should focus on the long-term effectiveness of these interventions, the scalability of technology-based solutions, and the integration of user feedback into the development process to ensure that these tools meet the evolving needs of individuals with ASD and their caregivers.

Imaging Informatics

Imaging Informatics employs advanced computational and imaging techniques to enhance diagnostic accuracy and understand neurobiological underpinnings of ASD^{106,274}. This discipline uses tools such as Magnetic Resonance Imaging (MRI), functional connectivity MRI (fcMRI), and EEG, alongside machine learning algorithms, to analyze brain images for diagnostic and therapeutic insights. For instance, deep learning models applied to EEG spectrogram images and fcMRI have demonstrated high accuracy in ASD diagnosis^{275–277}. The exploration of the ABIDE database for ASD patient identification^{278–281} and the development of a Functional Random Forest model to determine ASD subtypes²²⁸ further illustrate the critical role of imaging informatics in advancing precision medicine for ASD. Moreover, the integration of

structural and functional MRI data offers a nuanced view of ASD, aiding in the identification of neurobiological markers and potentially guiding precision medicine²⁸². Studies on structural brain imaging^{283,284} and neurocognitive testing²⁸⁵ aim to further refine ASD diagnosis and treatment approaches. These advancements highlight the vital role of imaging informatics in the early detection, accurate diagnosis, and tailored intervention of ASD, marking significant strides towards understanding its complex etiology.

Public Health Informatics

Public health informatics is the application of information technology and data science to improve public health outcomes and services.¹⁰³ It involves the use of informatics in areas such as surveillance, prevention, preparedness, and health promotion, aiming to improve public health outcomes through enhanced decision-making processes. Public health informatics reveals significant insights into how digital health interventions, disparities in health access, support methods, and telehealth can impact ASD care and outcomes.

Digital and mobile health interventions, as evidenced by studies on Twitter's (X) role in ASD support²⁸⁶ and the development of a public transport planning tool for ASD individuals²⁶² illustrate the power of technology in enhancing education, engagement, and support. These platforms facilitates communication within the ASD community and address specific challenges, offering tailored solutions for improved quality of life. New methods for ASD support, such as the participatory design in monitoring technology development²⁸⁷, and the efficacy of telehealth interventions^{232,233}, demonstrate the importance of tailored and remote solutions. These approaches cater to the specific needs of the ASD community and expand the reach of interventions, particularly in underserved areas²³.

Health disparities significantly affect ASD diagnosis and treatment access. Studies highlighted delays in diagnosis among African American children and service access challenges^{288,289}. These findings underscore the necessity of targeted interventions to ensure equitable health outcomes. Moreover, the evaluation of the

M-CHAT-R screening tool revealed its linkage with risk factors like geographic location and parental education, emphasizing the need to bridge gaps in ASD diagnosis and care²⁹⁰. Another study employing the M-CHAT-R in an urban pediatric setting showed how web-based and mobile applications could mitigate disparities²⁹¹, further advocating for digital solutions in public health challenges. One study highlighted the higher rates of suicide attempts and suicides among individuals with ASD compared to those without³². This study underscores the urgent need for tailored suicide prevention strategies that consider psychiatric comorbidities among individuals with ASD.

Collectively, these studies highlight the critical role of public health informatics in addressing ASD-related public health challenges. By leveraging digital tools, addressing disparities, and employing new and telehealth solutions, public health informatics offers a promising pathway to minimize diagnostic delays and improve outcomes for individuals with ASD. The integration of public health informatics into ASD screening and early detection strategies calls for a concerted effort to harness informatics in enhancing access to diagnostic and intervention services, emphasizing the importance of inclusive and equitable health practices.

Telehealth

Telehealth or telemedicine facilitates remote health services delivery, aiming for health promotion, disease management, and disability prevention^{96,167}. The scoping review of telehealth and ASD reveals significant advancements and varied applications across different regions and contexts. Studies from Australia, Canada, the United States, and several other countries highlight telehealth's versatility in addressing challenges such as language assessments, coping during the COVID-19 pandemic, mask-wearing training, telemedicine for diagnosis, and cognitive behavioral therapy for insomnia among children with ASD. One study's findings suggest that telehealth is a reliable and feasible modality for language assessments in children with autism, indicating its potential as a primary or adjunct service model²⁹². Other work underscores the importance of telehealth and care models in supporting autistic individuals during challenging times like the COVID-19 pandemic²⁹³. These studies collectively emphasize the adaptability

of telehealth services to meet specific needs, such as mask-wearing training²⁹⁴ and telemedicine for ASD diagnosis^{295,296}. A notable study highlighted telemedicine's role in early detection of ASD, combining questionnaire screening and diagnostic tools with home video screenings, enhancing access and enabling earlier ASD detection²⁹⁷. Another research employed video conferencing for rural families, significantly reducing the time from symptom identification by parents to clinical diagnosis, addressing the accessibility challenges in remote areas²⁹⁸.

Moreover, telehealth has been shown to be a feasible and satisfactory method for delivering interventions, such as cognitive behavioral treatment for insomnia²⁹⁹, and has potential for broader implementation in ASD assessments and interventions^{300–302}. Recent studies further validate telehealth's effectiveness in delivering interventions for ASD, highlighting its utility in parent coaching, improving social-pragmatic skills, and managing sleep disturbances^{232,233,238,303}. These findings illuminate the significant potential of telehealth as a sustainable and adaptable tool for supporting individuals with ASD. The studies underscore the importance of addressing technological and communication challenges to enhance telehealth's accessibility and efficacy. Future research should focus on optimizing telehealth delivery models, evaluating long-term outcomes, and exploring its application in other aspects of health care beyond autism spectrum disorder.

Research Gaps and Future Directions

The exploration of ASD within the realm of health informatics signifies advancements towards better understanding of this multifaceted condition. The last fifteen years have shown focused effort towards the early detection and diagnosis of ASD, alongside the development of assistive technologies designed to enhance the clinical management of the disorder and support individuals affected by it. Despite these noteworthy advancements, the research landscape is marred by limitations that stem from the preliminary nature of these studies.

One of the primary challenges is the lack of implementation of research findings across varied clinical settings and patient demographics. This limitation is compounded by an insufficient formal evaluation framework capable of accommodating the diverse manifestations of ASD. The inherent variability in symptom presentation and severity associated with ASD underscores the necessity for research methodologies that are both adaptable and inclusive. Current studies often operate on a relatively small scale and may not accurately reflect the broader ASD population, resulting in findings that are potentially narrow in scope and applicability. Moreover, the early stage of much ASD research means that many approaches and technologies have not undergone rigorous, large-scale validation. This raises questions about their effectiveness and reliability when applied in real-world clinical contexts. The heterogeneity of ASD, characterized by a spectrum of cognitive, social, and behavioral symptoms, necessitates a diverse array of diagnostic and therapeutic approaches. However, the current body of research often fails to address this need, limiting the potential for these innovations to effect meaningful change in patient outcomes.

Additionally, there is a noticeable gap in longitudinal studies that track the long-term efficacy of early detection methods and assistive technologies. Such research is crucial for understanding how these interventions impact individuals with ASD over time, including their ability to integrate socially, achieve academic and vocational success, and maintain an improved quality of life. The reliance on data extraction methods and diagnostic practices that have not been sufficiently evaluated across a wide range of patient cohorts further complicates the landscape. This can limit generalizability of research findings and can hinder the development of standardized, evidence-based protocols for the management of ASD. As a result, there is an urgent need for more expansive and inclusive research efforts that can bridge these gaps. Future studies should aim to implement broader evaluations, encompassing diverse patient populations to ensure that findings are reflective of the entire spectrum of ASD. By addressing these research limitations, the field can move towards more effective, personalized approaches to diagnosis and treatment that meet the needs of all individuals with ASD.

After analyzing the current literature and categorizing common research objectives by informatics subfield as shown in **Figure 2.4**, this review highlights three main areas for focused future research endeavors: (1) information sharing, (2) patient education and engagement, and (3) mitigating health disparities among individuals with ASD. ASD's complexity is compounded by frequent comorbidities and the necessity for patients to consult multiple healthcare providers for varied therapies and treatments. These individuals possess extensive health records, chronicling years of clinical observations and essential details regarding their ASD diagnosis. Therefore, it is crucial to facilitate health information exchange (HIE) to ensure clinicians have access to patient records, thereby optimizing patient care. Moreover, the existing gaps in our understanding of ASD underscore the need for systematic and thorough information aggregation to amplify research efforts and expand our knowledge base about the disorder. Using complete patient records could unveil insights about ASD and foster advancements in diagnosis and treatment strategies.

Furthermore, engaging patients and their families in healthcare decisions is paramount. Given the complexities associated with ASD in the wide array of presentations and diverse set of treatments and therapies, informatics could play a role in identifying care disparities and educational voids. Empowering patients with education, resources, and optimal care could bridge these gaps, leading to more effective care management and enhanced outcomes. As such, addressing these identified research voids could significantly contribute to the advancement of ASD care, enabling individuals with ASD to achieve their fullest potential and seamlessly integrate and navigate the complexities of adulthood and surmount the hurdles associated with ASD.

2.5 Conclusion

This scoping review explored the intersection of health informatics and ASD research over the past fifteen years. It has identified significant strides in diagnosis and the development of assistive technologies, pointing toward a future where technology and data-driven insights play a role in understanding and managing ASD. The literature reveals numerous practical efforts within the ASD community employing informatics. Given the increasing prevalence and escalating costs associated with ASD, this research area

is both timely and critical. The focus has predominantly been on early detection, diagnosis, and intervention, driven by evidence suggesting that early treatments can significantly improve outcomes. However, it also highlights the early stages of many innovations, identifying a need for broader implementation, rigorous validation across diverse populations, and long-term efficacy studies. The identified research priorities—information sharing, patient education and engagement, and addressing health disparities—set a clear agenda for future investigations. Addressing these areas will be crucial for leveraging health informatics to its full potential, ensuring that advancements in ASD research translate into tangible benefits for individuals with ASD and their families. The path forward requires a multifaceted approach that embraces the complexity of ASD, fosters interdisciplinary collaborations, and remains committed to inclusivity and equity in healthcare.

Chapter 3: Aim 1-

Breaking Down Barriers: A Qualitative Focus Group Study on Challenges Faced by Caregivers of High-Needs Children

List of Chapter Acronyms

ADHD = Attention-Deficit/Hyperactivity Disorder
ASD = Autism Spectrum Disorder
CFIR = Consolidated Framework for Implementation Research
ERIC = Expert Recommendations for Implementing Change
NIH = National Institutes of Health
RADx-UP = Rapid Acceleration of Diagnostics-Underserved Populations
RIPIN = Rhode Island Parent Information Network

Preface

A version of this chapter is in preparation as a manuscript for submission.

This chapter lays the foundation for Aim 1, marking the qualitative cornerstone of this dissertation by examining community needs through engaging caregivers in Rhode Island. Using focus groups, this inquiry delves into the myriad challenges these caregivers faced during the COVID-19 pandemic, with an emphasis on the emotional and social impacts, obstacles to healthcare access, and mental health resource needs. While the initial focus was on pandemic-related issues, the analysis broadens to encompass the enduring mental health needs, showcasing how the pandemic has intensified existing challenges, thereby underlining its relevance to this work. This chapter delves into the experiences of caregivers for children requiring extensive support due to various conditions, including Autism Spectrum Disorder (ASD). This study was conducted in partnership with the Rhode Island Parent Information Network (RIPIN), a community organization that provides support and advocacy for families of children with high-needs. This study carried out focus groups to explore barriers to accessing health services and the broader challenges these families face, particularly during the pandemic. Through directed content analysis and thematic analysis, using the Consolidated Framework for Implementation Research (CFIR) as a guiding framework, the study identifies key themes related to service access, mental health, and the social-emotional impacts on children and their

caregivers. Special attention is given to the experiences of caregivers for children with ASD, highlighting the pandemic's magnified impact on their well-being and access to necessary services. The chapter concludes with suggestions for improving service adaptability, mental health support, social isolation mitigation, and education on available resources.

3.1 Introduction

Children with high-needs refer to those who require significant assistance and specialized services due to a range of physical, emotional, developmental, or educational challenges¹⁻³. These children often have conditions that necessitate ongoing support from healthcare providers, educators, and caregivers to manage daily living tasks, achieve developmental milestones, and maintain their health and well-being. The term encompasses a wide spectrum of needs, including but not limited to, chronic health conditions, severe learning disabilities, emotional or behavioral difficulties, and complex developmental disorders³.

ASD exemplifies a condition that classifies a child as having special healthcare needs or as "high-needs"^{8,304,305}. ASD is a neurodevelopmental disorder that involves impairments in social communication and interaction, coupled with repetitive behaviors and restricted interests⁴. The spectrum nature of ASD implies that the condition affects individuals differently and to varying degrees. Some children with ASD may require minimal support, while others may need interventions involving speech therapy, occupational therapy, behavioral therapy, and educational support tailored to their specific needs^{155,306}. Children with ASD, like other high-needs children, often require a multidisciplinary approach to care and support that addresses their unique challenges and promotes their development and well-being. This may include personalized education plans, therapy sessions, and medical care, as well as accommodations at home and in the community to enable them to participate fully and meaningfully in their environments¹⁵⁵. The designation of a child as "high-needs" highlights the importance of providing individualized support and services that cater to their specific requirements. It emphasizes the need for a collaborative effort among caregivers, healthcare providers, educators, and community services to ensure that these children can achieve their potential and lead fulfilling lives³⁰⁷.

Understanding the multifaceted needs of children with high-needs is crucial in designing effective support systems that cater to their unique challenges. These children often require health, educational, and emotional support due to various conditions, including chronic health issues, disabilities, and developmental disorders. Engaging with caregivers provides invaluable insights into the lived experiences, barriers to accessing necessary services, and the facilitators that enhance the well-being of these children and their families³⁰⁸. Qualitative analysis, through methods such as community focus groups with caregivers, can uncover the needs and challenges faced by children with high-needs. This approach allows for the exploration of personal narratives, providing a detailed understanding of the daily experiences, obstacles, and supportive factors encountered by these families. Such qualitative insights are instrumental in identifying gaps in current support systems and in guiding the development of interventions that are both empathetic and effective, directly addressing the specific needs highlighted by caregivers.

The National Institutes of Health's Rapid Acceleration of Diagnostics-Underserved Populations (RADx-UP) encompassed a series of research projects throughout the United States, focusing on accessibility of services, the social and emotional impacts, and the resource needs of high-needs children and their caregivers during the COVID-19 pandemic^{309,310}. This RADx-UP study was embedded within a broader state-level effort in Rhode Island, which pursued three primary objectives: (1) leveraging the state's health information infrastructure to analyze access to and the adoption of COVID-19 testing and vaccination, (2) pinpointing obstacles to their widespread uptake, and (3) identifying strategies to overcome these challenges through community-engaged methods.

This study broadens its focus to examine the broader COVID-19-related impacts on children with high-needs by engaging with caregivers and leveraging state health information exchange data. It aims to understand the multifaceted effects of the pandemic on this vulnerable group through a dual approach. First, by conducting in-depth discussions with caregivers, the study seeks to gather insights into the unique challenges and experiences faced by children with high-needs during the pandemic. Second, identify barriers to healthcare services, and explore opportunities for improving access and outcomes. This approach

allows for a better understanding of the pandemic's impact on children with high-needs and the development of targeted strategies to address these challenges.

3.2 Methods

Overview

Figure 3.1 provides an overview of the study approach and strategy. This study was conducted in partnership with the RIPIN, a local organization dedicated to serving children with high-needs and their families. By collaborating with RIPIN, we sought to engage directly with caregivers through focus groups to explore the specific barriers they encounter in accessing SARS-CoV-2 testing and COVID-19 vaccinations for their children. The focus on these health services was part of a broader objective to understand the general challenges, needs, and barriers that families of high-need children face, especially during the COVID-19 pandemic. The pandemic has undeniably exacerbated the social and emotional challenges for this vulnerable population, highlighting the necessity to assess the impact. The goal extended beyond the immediate concerns related to COVID-19, aiming to understand the overall experiences of caregivers and the additional resources and services needed to support them. This includes a special focus on the experiences of caregivers of children with ASD given the unique challenges this group faces in accessing services and support.

To analyze the data collected from these focus groups, CFIR was used as a guiding framework. CFIR offers an approach to identify and evaluate the various factors that influence the implementation and effectiveness of interventions^{120,121}. By coding the data through the constructs and topics within the CFIR domains, themes could be systematically identified that emerged from the caregivers' narratives. Subsequently, a deeper thematic analysis was conducted to describe these themes in detail, providing a rich understanding of the caregivers' experiences and the barriers they face^{133,134}. The choice of CFIR for directed content analysis and the employment of thematic analysis were instrumental in dissecting the complex interplay of factors affecting the accessibility and effectiveness of services for children with high-needs³¹¹. CFIR's

structured approach facilitated the identification of key areas for intervention, while thematic analysis offered insights into the caregivers' perspectives and experiences^{312–314}.

In addition to employing a directed content analysis to systematically categorize the qualitative data gathered from focus groups, a thematic analysis was also conducted. This subsequent analysis aimed to elucidate specific themes emerging from the discussions, thereby enriching understanding of the caregivers' experiences and perspectives³¹⁵. By integrating both approaches, the study was poised to uncover deeper insights into the social and emotional impacts faced by families of high-needs children. These insights guided the formulation of targeted suggestions and strategies to address the identified needs, laying a foundational basis for subsequent aims of the research.

This work culminates in proposing suggestions to addressing the identified challenges. By drawing on the insights gained from caregivers and the analytical frameworks employed, the goal is to offer practical recommendations that can enhance the support systems for children with high-needs and their families. This study contributes to the ongoing efforts to improve healthcare and access to support services for one of the most vulnerable populations, emphasizing the importance of caregiver perspectives in shaping effective interventions.

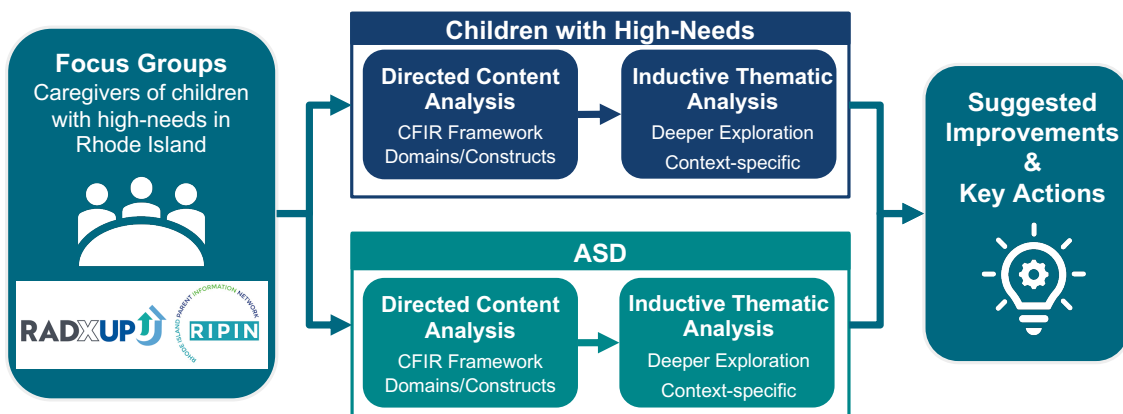


Figure 3.1: Overview of Study Approach

Rhode Island Parent Information Network (RIPIN)

The RIPIN is a nonprofit organization dedicated to providing support and resources to families and individuals across Rhode Island, particularly those navigating the complexities of raising children with special healthcare needs, disabilities, and educational challenges. RIPIN offers a wide range of services aimed at empowering parents, caregivers, and individuals through education, advocacy, and direct support. RIPIN's core mission revolves around ensuring that individuals and families have access to the necessary information and resources to make informed decisions about healthcare, education, and their overall well-being. The organization plays a pivotal role in connecting families with community resources, providing guidance on navigating healthcare and education systems, and advocating for policies that support the needs of children with high-needs and their families.

One of the key strengths of RIPIN is its approach to support, which includes one-on-one consultations, workshops, training sessions, and support groups. These services are designed to enhance the capacity of families and individuals to advocate for their needs effectively and to foster a community of support among those facing similar challenges. Furthermore, RIPIN collaborates closely with healthcare providers, educational institutions, and other community organizations to bridge gaps in services and to promote an integrated approach to supporting families. This collaborative effort highlights RIPIN's commitment to creating a more inclusive and supportive environment for all Rhode Islanders, especially those with special needs. RIPIN serves as a critical resource and advocate for families and individuals with special needs in Rhode Island, offering a range of services designed to empower, educate, and connect them with the resources needed to thrive. This study adopted a community-centered approach, in collaboration with RIPIN, and played an integral role in recruiting participants and facilitating focus groups^{316,317}. This partnership allowed for direct engagement with caregivers of children with high-needs, which has been previously documented to provide unique insights into familial needs that are not readily apparent through data analysis alone.

Focus Group Execution

The research methodologies employed in this study received approval from the Brown University Institutional Review Board. With assistance from RIPIN, Brown University research personnel conducted virtual focus groups from March 2022 through December 2022. These sessions, lasting between one to one and a half hours, were designed to elicit caregiver perspectives. The discussions revolved around general experiences during the COVID-19 pandemic and more specific interactions with testing and vaccination processes. Additionally, focus groups probed into the social and emotional impacts of the pandemic and the resource and service needs of families with high-needs children. For a structured guide to the focus group discussions, see **Table 3.1**, which provides a detailed outline of the focus group questions, with the current analysis concentrating on the Social/Emotional Impact section.

Following the focus group discussions, an optional survey was sent out to participants to gather additional feedback and vital information. The purpose of this survey was to collect demographics, housing, education, and other COVID-19 and disease-related information required by the National Institutes of Health (NIH). This survey was distributed via a link in the video call chat at the end of each session, as well as through a follow-up email to ensure all participants had the opportunity to contribute further insights. The survey data were stored and analyzed in a secure environment to maintain the confidentiality of participants' responses and to ensure the integrity of the research findings.

Table 3.1: High-needs Children Caregiver Focus Group Questions

Topic	Questions
1 General COVID-19 Questions	• What is your current opinion of the pandemic? What do others that live in your home think? What do your neighbors, or friends think?
2 Mask Requirements	• What resources do you use to learn about the pandemic? • What are your thoughts on the mask requirements? • When do you feel comfortable not wearing your mask? When do you feel like you need to wear your mask? • Has your opinion changed after getting vaccinated? • What are your thoughts on people who wear their masks? What about those who don't use their masks?
3 Access to Testing	• What do you think about getting COVID-19 tested at this point in the pandemic? • If you had to get tested, how would you go about it? • After receiving your +/- result, did your behavior change in any way? How?
4 Vaccinations	• If you have been vaccinated, would you like to share your personal experience? • If you haven't been vaccinated, can you share why? What can you share about your neighbors', friends', and family's experiences?
5 Social/Emotional Impact	• Can you please share if there have been any social or mental health related impacts throughout the COVID-19 pandemic for your children? • What challenges have you and your children experienced as the pandemic has progressed? • What were the barriers to accessing needed resources and services for your children? • Do you feel like there are additional mental health and social resources and services needed as a result of the challenges faced throughout the COVID-19 pandemic?
6 Open-Ended Discussion	• How could RIPIN further support you?

Participant Eligibility and Consent

Participants were considered eligible for the study based on several criteria: (1) residency in Rhode Island, (2) being 18 years of age or older, and (3) having a child or dependent with high-needs as identified and screened by RIPIN. Informed consent was obtained through two avenues: (1) registration on the chosen video conferencing platform, which involved agreeing to the terms and conditions, and (2) an additional verbal agreement at the commencement of each focus group session.

Compensation and Confidentiality

To value the contribution of the participants' time and insights, compensation was provided. This included financial reimbursement and the opportunity for participants to pose questions directly to local health representatives, thereby facilitating a bidirectional exchange of information and concerns.

Research Team Involvement

The research team collaborated with the community organization to assist in facilitating each focus group. Collaborating to facilitate and moderate the focus groups helped ensure an unobtrusive environment where caregivers could freely share their experiences. The methods adopted for this study were designed to prioritize the voices of those directly affected by the pandemic while ensuring ethical and respectful engagement with the community. The approach aimed to produce findings that are both grounded in real-world experiences and beneficial for policy and practice aimed at supporting high-needs families.

Data Analysis

Phase One: Directed Content Analysis

The focus group data, captured via video conferencing, were transcribed verbatim and translated as needed by a professional third-party service. The analysis was structured in two phases to ground the work using a traditional framework and then provide more detailed findings to suggest improvements. In the first phase, we applied directed content analysis to pinpoint barriers to access and resource needs. This method employed a deductive coding approach, guided by existing theory, and allowed for the inductive development of new codes from uncoded content³¹¹. The coding was structured around the CFIR domains and their corresponding subconstructs, which include: (1) intervention characteristics, (2) outer policy context, (3) inner context, (4) characteristics of individuals targeted in implementation, and (5) implementation process¹³². Each transcript was coded by individual analysts using this established framework. To assure consistency and methodological rigor, groups of two to three analysts then cross-

coded the transcripts. The finalized codes were systematically entered into NVivo, a qualitative data management software, to facilitate organization and analysis³¹⁸.

Phase Two: Thematic Analysis

The second phase involved thematic analysis, which examined the coded data for emergent patterns across and within the CFIR codes. This process was aimed at constructing a narrative that captured the key trends in implementation^{133,134,319}. Under the supervision of a secondary analyst, the primary analyst undertook the task of reviewing, defining, and naming the themes. To illustrate these themes, specific participant quotations were selected for their representative nature.

Word Cloud Generation

As part of the thematic analysis, a word cloud visualization was created to further illustrate the prevalence of certain themes and terms within the focus group data^{320,321}. A word cloud is a visual depiction of text data where the size of each word indicates its frequency of occurrence from the focus group transcripts³²². This word cloud analysis was based on the responses and excerpts from the focus groups, with a specific focus on the discussion and topics of interest in this study, which centered on the Social/Emotional Impact questions (**Table 3.1**). NVivo was used to generate a word cloud by using its text analysis capabilities where the most frequently occurring words and phrases from the coded and thematic content were extracted. The extracted terms were then input into a word cloud generator, which created a visual depiction of the data. Words and phrases that were more common appeared larger in the word cloud. To ensure clarity and relevance, common English stopwords (e.g., "the", "and", "is") were excluded from the word cloud. Additionally, terms that were similar in meaning were grouped to avoid redundancy.

The size of each term within the word cloud was made proportional to its frequency, visually representing the relative emphasis placed on different themes by the study participants. This method of visualization served as an effective supplementary tool to the thematic analysis, offering a quick and intuitive understanding of the primary concerns and needs identified during the discussions. Furthermore, the word

cloud was integrated into the study as a figure, providing a visual summary that complements the qualitative findings. This approach facilitated a more engaging presentation of the data and highlighted the critical areas of focus for interventions aimed at supporting high-needs families during the pandemic and beyond.

Suggestions/Implementation Strategies

Upon the identification of themes, we shifted focus to discern specific implementation barriers. Using the Expert Recommendations for Implementing Change (ERIC) as a guide, we mapped out potential strategies to address these identified barriers^{122–124}. Each strategy was then named, defined, and specified in detail, aligning with the procedural guidance³²³. This final step was critical in translating thematic insights into actionable recommendations for addressing the implementation challenges uncovered during the analysis.

3.3 Results

Focus Group Participants

Fourteen focus groups were conducted, involving an average of 5-6 participants per group, totaling 81 participants. In addition to the focus group discussions, 61 out of the 81 participants, representing 75.31%, completed the follow-up survey. **Table 3.2**, informed by the survey data, presents a demographic breakdown of the focus group participants, highlighting most female caregivers with an average age of 45, and a diverse educational background ranging from some college to advanced degrees. The table also reflects the race and ethnicity of participants, showing a predominance of White non-Hispanic caregivers, along with representation from Black or African American individuals and other ethnic groups.

<i>Table 3.2: Demographic and Educational Profile of Focus Group Caregivers</i>		
Caregiver Characteristics	N (%)	
Total	81	
Sex		
Male	2	(2.5%)
Female	59	(72.8%)
Unknown	20	(24.7%)
Age (years)		
Average	45	(SD = 9.65)
Age Range	26-69	
20-29	3	(3.7%)
30-39	14	(17.3%)
40-49	25	(30.9%)
50-59	14	(17.3%)
60-69	4	(4.9%)
Unknown	21	(25.9%)
Race		
American Indian or Alaska Native	2	(2.5%)
Black or African American	13	(16.0%)
White	43	(53.1%)
Other	3	(3.7%)
Unknown	20	(24.7%)
Ethnicity		
Hispanic	7	(8.6%)
Non-Hispanic	53	(65.4%)
Unknown	22	(27.2%)
Education		
No Diploma	2	(2.5%)
High School Graduate	4	(4.9%)
Some College	23	(28.4%)
Bachelor's Degree	16	(19.8%)
Advanced Degree	15	(18.5%)
Unknown	21	(25.9%)

Directed Content Analysis

Initially, a directed content analysis was carried out on all 14 transcripts, with cross-coding validation performed by 2-3 coders for each transcript. Responses to the Social/Emotional Impact questions, as well as any related responses found throughout the transcripts were extracted and subjected to further analysis. Four predominant codes were identified that aligned with the focal questions and topics (Social/Emotional Impacts) derived from the CFIR subconstructs within three domains: (1) Intervention Characteristics (emphasizing Adaptability), (2) Outer Setting (focusing on Patient Needs & Resources), (3) Inner Setting (concerning Available Resources), and (4) Characteristics of Individuals (Other Personal Attributes). In the thematic analysis phase that followed, six primary themes emerged as focal areas, which are elaborated in the subsequent sections. These themes are emphasized by representative quotes within the main text to provide context and depth to the findings. To enhance validity, additional quotes are provided in the Appendix. In adherence to confidentiality standards, all quotes have been de-identified to protect the identities of the participants.

CFIR offers a lens through which to analyze the multifaceted aspects of implementation within healthcare settings. By focusing on subconstructs, the framework facilitates a better understanding of the factors influencing the effectiveness of interventions³²⁴. Below each CFIR subconstruct of interest identified in the analysis is described, adding detail to their roles and implications.

Intervention Characteristics (Adaptability): This subconstruct emphasizes the importance of interventions being adaptable and flexible to meet the unique needs of high-need children and their caregivers. The analysis stressed the necessity for customizable approaches that can be adjusted in response to changing requirements, highlighting adaptability as a key determinant of an intervention's success.

Outer Setting (Patient Needs & Resources): This subconstruct centers on the external economic, political, and social contexts within which an organization operates. The analysis uncovered significant barriers to accessing specialized services and resources, highlighting the external pressures and community needs that

play a role in shaping service provision. It highlighted the critical gaps in healthcare accessibility and the urgent need for tailored solutions to address these disparities.

Inner Setting (Available Resources): Focusing on the internal climate within an organization, this aspect examines the readiness and available resources to adopt and implement changes. The evaluation pointed to various internal factors that either facilitate or hinder the accessibility of services, such as organizational infrastructure, culture, and the availability of resources. This insight into the inner workings of organizations provides a foundation for understanding the challenges and opportunities in enhancing service delivery.

Characteristics of Individuals (Other Personal Attributes): Here, the focus is on the attributes of individuals, including their knowledge, beliefs, and personal experiences. The resilience of caregivers and children, along with their capacity to navigate complex systems, emerged as critical factors. These personal attributes significantly influence how effectively individuals can engage with and benefit from existing support structures.

Thematic Analysis

Transitioning from these foundational insights, the thematic analysis phase further distilled the information into more detailed themes. By examining responses and identifying patterns related to the Social/Emotional Impact questions, the analysis shed light on the complex dynamics at play. These themes, derived from the CFIR subconstructs, provided a deeper understanding of the challenges and opportunities within the caregiving ecosystem, leading to actionable insights on improving support for high-need families. **Table 3.3** presents the themes derived from the thematic analysis, along with their corresponding CFIR constructs, showcasing the direct correlation between the identified themes and the foundational constructs of the CFIR framework. This table serves as a crucial link, illustrating how thematic insights align with established implementation science principles. Following the overview provided in Table 3.3, the subsequent sections delve into more detailed descriptions of each theme. Framed within the broader context of pre-pandemic

challenges, these themes highlight the systemic inadequacies in providing for high-needs children and their families. The pandemic magnified these issues, highlighting the urgent need for systemic changes to address the deeply rooted problems in service provision and support for this vulnerable population.

Table 3.3: *Correlation Between Thematic Analysis Themes and CFIR Constructs*

Theme	CFIR Construct
Essential Support and Access to Services: Beyond the Pandemic	Outer Setting - Patient Needs & Resources
Navigating Mental Health: Needs and Gaps	Characteristics of Individuals - Other Personal Attributes
Social Isolation and Regression	Characteristics of Individuals - Other Personal Attributes
Need for Resources and Education on Services and Mental Health Therapy	Inner Setting - Available Resources
Barriers to Accessing COVID-19 Health Services	Intervention Characteristics – Adaptability & Outer Setting - Patient Needs & Resources

Theme 1: Essential Support and Access to Services: Beyond the Pandemic

This theme focuses on the critical need for resources and support tailored to caregivers and children, especially those with high-needs, highlighting a gap that has existed long before the pandemic and has since widened. It addresses the overarching need for a network of resources and support systems specifically designed for caregivers of special and high-needs children and the children themselves. It encompasses the need for accessible mental health services, educational support, therapeutic services, and respite care, all of which have been highlighted by the pandemic as essential yet often insufficiently available or accessible. The theme emphasizes the ongoing struggle to secure these resources and the urgent need for systemic improvements to meet these foundational needs effectively. Caregivers express a profound need for more accessible and support services to aid in the care and development of their children.

Supporting Quotes:

- *“The difficult part early on was during isolation no school. My son received no vital services which was understandable, but it set him back so far.”*
- *"My daughter she was in a psychiatric facility for most of the time and it was due to all the lack of services the lack of school and virtual. Our kiddos didn't have a plan when this happened. There was no plan in place to keep them out of the hospital. I feel like the services that we've had been well for our kind of life we weren't skimmed to none anyway."*

- *"Still even for us out of school for us parents to get services for our children like my son right now he's an adult. It's harder to get services for my son now. I have called places and it's one to two years to get services at home now."*
- *"I feel like the services that we've had... were slim to none anyway. We always were scrambling for school placements, and staff at home to help. I feel like the school services, and the home services combined, and community resources have failed. I think the pandemic just put the brakes on it and spotlighted this."*
- *"I could imagine all the parents that are going through what I'm going through with my son with behavior issues that can't get services because there's a waiting list for a year and two years."*
- *"There are a lot of disruptions to therapies..."*
- *"Then I just finally recently was able to get her back into her outside OT so that's been helpful but even then, they're so now inundated with all these people coming back I can only get her seen twice a month instead of once a week."*

Theme 2: Navigating Mental Health: Needs and Gaps

This theme delves into the mental health challenges faced by both caregivers and their special needs children, exacerbated by the pandemic but also deeply rooted in pre-existing systemic gaps in mental health support. It uncovers the emotional and psychological toll on families, emphasizing the heightened need for accessible, specialized mental health services. The pandemic has intensified these needs and spotlighted the scarcity of resources tailored to the unique challenges of this community. Caregivers expressed concerns about their children having increased anxiety, depression, and stress levels due to isolation, disruption of routines, and lack of services. This theme calls for urgent action to bridge these gaps and provide mental health care and support. Participants describe the intensified mental health challenges during the pandemic and the continuous struggle to find adequate support.

Supporting Quotes:

- *"We have things in place, but we've needed so much more, and they have not been easily accessible." [speaking about mental health services]*
- *"I'm also concerned with the anxiety that it creates for special needs kids and kids that have mental health in general."*
- *"The mental, emotional challenge... emotionally he gets very depressed and stressed."*
- *"He developed depression and anxiety during COVID."*

- *"Just when we were going over the hump, then the pandemic started, and it made him so anxious, and it made him more depressed."*
- *"I just want to jump in and add that mental health services as we all know there's a crisis, but it was and is still extremely difficult to access."*
- *"It just seems like there's missing a lot of the mental health piece."*
- *"I'm also concerned with the anxiety that it creates for special needs kids and kids that have mental health in general."*
- *"I think they exasperated their mental health issues. I really do." [speaking about education support]*
- *"I think it's created a lot of anxiety and over the unpredictable future. I just think if anyone had preexisting anxiety and depression, I think it's amplified, and it takes a lot to be upbeat to be honest with you with the way the world is."*
- *"The schools need to start helping our kids with special needs" - referring to the lack of mental health support within educational settings.*
- *"You couldn't get a bed at [pediatric psychiatric hospital]. Everything was stretched. Majority of it was special needs kids because they left them high and dry" - highlighting the strain on mental health services.*
- *"I think it exasperated their mental health issues. I really do."*
- *"For us, you can be so careful about the health, but mental health and emotional health is also part of health."*

Theme 3: Social Isolation and Regression

This theme captures the emotional resilience displayed by caregivers and their children in the face of prolonged social isolation and the disruption of social supports. It emphasizes the variety of coping strategies adopted by families to navigate these challenges, while also highlighting the emotional cost of isolation and the critical need for enhanced social support mechanisms. This theme encapsulates the profound impact of social isolation due to pandemic restrictions, leading to significant regression in social skills and emotional development among high-needs children. Caregivers reported a noticeable decline in their children's ability to interact socially, exacerbated by the suspension of in-person educational and therapeutic services. The lack of physical social interaction delayed the children's social development and contributed to emotional distress, frustration, and increased behavioral challenges. Participants discussed

the emotional strain of isolation on their families and the creative strategies they employed to foster connection and maintain mental health.

Supporting Quotes:

- *"For him, he needs that diversion, community connections, he needs people, and socialization."*
- *"My son just was so frustrated pent up and was very tired of just having such limitations of socialization."*
- *"My daughter who is autistic in ADHD as well she lost all her outside therapy... She can't physically process that."*
- *"She regressed so much with her social skills because she didn't see anybody."*
- *"Bringing her out into a public area now is absolutely terrifying because I know how she melts down."*
- *"There was such a huge regression in her, and she just went from her being able to handle her situations to complete extreme outbursts to hitting and kicking and throwing and violence towards others and never harm to herself but always harm to others."*
- *"I wish there was more social opportunities... my son just was so frustrated pent up and was very tired of just having such limitations of socialization."*
- *"There were challenges socially. She has some social stuff to begin with and to actually have pulled her back. Virtual learning if I were not on the side of her coaxing her and following up after it was a struggle for her... The social piece was not healthy for her."*

Theme 4: Need for Resources and Education on Services and Mental Health Therapy

This theme captures the urgent need for increased resources and education regarding available services and mental health therapy options for families of high-needs children. Caregivers expressed a lack of awareness and difficulty accessing specialized services, support groups, and mental health resources tailored to their unique circumstances. The pandemic has intensified this need, highlighting the gaps in the support system and the importance of effective communication and outreach to ensure families can access the help they require. This theme emphasizes the critical gap in resources and information for families navigating the complex landscape of services and support for high-needs children, especially in the context of the pandemic.

Supporting Quotes:

- *“You know that I called [pediatric psychiatric hospital] to get him in the CADD program when COVID was going on. I waited for eight months to get him in [pediatric psychiatric hospital]. The schools need to start helping our kids with special needs.”*
- *“Advocating for lost services during that during COVID. I know for example one of my sons did not get his services for the first three months as it was.”*
- *“I think our special needs services that can help kids to cope with it whether it be parent zoom sessions like this one. Or whether it just be resources that the parents and schools can use to help with them coping with the things like the anxiety because being in person for kids like mine that was critical. They lost a lot of what was on their IEPs and what their needs were because we were shut down.”*
- *“As a mother of a 17-year-old, I think that there needs to be more support services... or someone to help parents transition to adulthood and the steps.”*
- *“Education... I think they dropped the ball and the expectations for kids with special needs. They asked a lot more of them without any support.”*
- *“The special needs kids, they always fall by the wayside. They're always neglected. They don't say their education. They're failing them every single day, no matter what district it is, they're failing them.”*

Theme 5: Barriers to Accessing COVID-19 Health Services

This theme focuses on the navigational challenges faced by many high-needs families for COVID-19 related health services. This theme reflects the specific obstacles faced by many of the caregivers when attempting to secure COVID-19 testing and vaccinations for their special and high-needs children. It encompasses logistical challenges, such as long wait times and unsuitable testing environments, alongside systemic issues like the lack of prioritization for high-risk populations and inadequate communication of available resources. The experiences shared by many of the participants reveal a complex interplay of logistical, emotional, and systemic obstacles that hindered timely and effective access to COVID-19 health services. These barriers involved logistical difficulties in scheduling tests or vaccinations and finding accessible locations in addition to emotional stressors as well, with reports of anxiety and distress related to potential exposure and the adequacy of care provided in these settings. Additionally, systemic barriers, such as lack of accommodations for children with special needs during testing and vaccination processes, were prevalent, highlighting a significant oversight in public health responses tailored to the needs of high-

needs populations. This theme validates the need for a more accessible and empathetic approach to public health planning and response, especially in catering to the needs of high-needs children and their caregivers. Caregivers voiced their struggles with obtaining timely COVID-19 tests and vaccinations, emphasizing the need for more accessible and accommodating healthcare services for their vulnerable children.

Supporting Quotes:

- *"I wish there had been a place that I could take him where people had worked with special needs children, and we could have had a little more time to get him adjusted to what we were going to do instead of holding him down and swabbing his nose it was traumatic."*
- *"Getting my son to test was very difficult being he needed something in his nose that did not go well at all. He would cry and fidget and it was a process of holding him."*
- *"We had to do the drive-up one and it was so much easier. Thinking about places that don't [have that option now]. You have issues with childcare, you can't go to an appointment with siblings and all this other stuff, to be able to just make an appointment and drive through with one child or multiple or whatever and just be able to do it was a lot easier when that was offered."*

Table 3.4: Overview of Key Themes on Social/Emotional Impact and Support Services for Families with High-needs Children During the Pandemic

Theme	CFIR Domain	Definition	Exemplar Quote
1 Essential Support and Access to Services: Beyond the Pandemic	Outer Setting - Patient Needs & Resources	Critical and ongoing need for a wide range of supportive resources and services for special needs children, a need made more acute by the pandemic.	• “I could imagine all the parents that are going through what I'm going through with my son with behavior issues that can't get services because there's a waiting list for a year and two years.”
2 Navigating Mental Health: Needs and Gaps	Characteristics of Individuals - Other Personal Attributes	Increased mental health challenges, including anxiety, depression, and stress, among high-needs children, pointing to a critical gap in tailored support services.	• “There are a lot of disruptions to therapies...” • “For him, he needs that diversion, community connections, he needs people, and socialization.” • “The mental, emotional challenge... emotionally he gets very depressed and stressed.” • “He developed depression and anxiety during COVID”
3 Social Isolation and Regression	Characteristics of Individuals - Other Personal Attributes	Substantial social skill regression and emotional distress due to prolonged social isolation and service disruption.	• “She regressed so much with her social skills because she didn't see anybody.” • “Bringing her out into a public area now is absolutely terrifying because I know how she melts down.”
4 Need for Resources and Education on Services and Mental Health Therapy	Inner Setting - Available Resources	Urgent need for enhanced access to specialized services and mental health resources, coupled with better education on these supports.	• “I think there's all of us going here that having a kid with special needs is a journey for itself, and it sometimes is so difficult to navigate the health system, education system.” • “As a mother of a 17-year-old, I think that there needs to be more support services... or someone to help parents transition to adulthood and the steps.”
5 Barriers to Accessing COVID-19 Health Services	Intervention Characteristics – Adaptability & Outer Setting - Patient Needs & Resources	This theme addresses the significant barriers caregivers face in accessing COVID-19 testing and vaccination services, highlighting systemic and logistical challenges.	• “I wish there had been a place that I could take him where people had worked with special needs children, and we could have had a little more time to get him adjusted to what we were going to do instead of holding him down and swabbing his nose it was traumatic.”

Word Cloud Analysis

Accompanying the narrative description of the themes, Figure 3.2 includes a word cloud that graphically depicted the relative frequency of terms identified in the focus groups and interviews. This visual served to immediately convey the most dominant concepts discussed by participants, providing an at-a-glance representation of their collective experiences and perceptions. The size of the terms in the word cloud was indicative of their frequency in the dataset. These visual findings were interpreted in conjunction with the more detailed thematic analysis, offering a multi-layered understanding of the data. The word cloud thus acted as both a standalone summary and a complementary piece to the overall analysis, linking visual data representation to qualitative insights. The word cloud in **Figure 3.2** highlights prevalent keywords such as “needs,” “services,” “school,” “struggling,” “help,” “therapy,” “disability,” and “issues,” among others. This graphical representation showcases the recurring concerns and topics raised during the focus groups and illustrates the alignment of these common themes with the results of the thematic analysis. The prominence of these terms visually encapsulates the core issues and needs identified by participants, offering a clear and immediate insight into the primary areas of focus that emerged from the discussions. Additionally, the word cloud prominently features the term "autism," indicating its frequent mention throughout the focus group discussions. Although the exact number of caregivers with children diagnosed with autism is not specified, this recurring reference highlights the significance of autism within the caregiver narratives. In the sections that follow, we will provide a more focused exploration, delving into the extracted responses that identified autism as a diagnosis. This detailed examination aims to shed light on the specific challenges, needs, and experiences of families navigating autism, further enriching our understanding of the thematic analysis findings.



Figure 3.2: Word Cloud Visualization of Key Terms Extracted from Focus Group Responses

Autism Spectrum Disorder (ASD) Analysis

In the examination of narratives from 14 focus groups, a significant emphasis emerged on the experiences of caregivers for children with ASD. This condition, affecting numerous families within our study, necessitates a specialized focus because of its prevalence and due to the challenges these families face, exacerbated by the COVID-19 pandemic. The decision to dedicate a separate section of our analysis to ASD stems from several critical observations:

- **Prevalence:** The terms "Autism," "ASD," "Autistic," and "on the spectrum" were mentioned a total of 52 times across all focus groups. Importantly, these mentions were unprompted, as caregivers were not specifically asked to disclose their child's condition. This high frequency of voluntary disclosure emphasizes the significance of ASD within the group, indicating a substantial portion of participants navigating the unique landscape of raising a child with ASD.
- **Impact of the Pandemic:** The pandemic has had a profound impact on all children, but those with ASD have faced particularly acute challenges. Disruptions to therapy and education, increased social isolation, and the amplified stress on caregivers highlight the need for focused attention on this group. The pandemic has brought to light these immediate challenges and has also amplified ongoing concerns regarding access to services, social acceptance, and the mental health of both children with ASD and their caregivers.
- **Word Cloud Analysis:** Supporting the qualitative findings, the word cloud generated from the larger analysis (**Figure 3.2**) visually emphasizes "autism" as a prominent term. This graphical representation further validates the importance of ASD as a key focus within the discussions, pointing to the condition's central role in the shared experiences of participants.

Given these factors, a specialized section on ASD is necessary to adequately address the experiences of these families. This focused analysis aims to explore the unique challenges and needs of children with ASD and their caregivers, providing insights into areas requiring targeted interventions and support. By

isolating and examining the specific experiences related to ASD, this research seeks to contribute to a more comprehensive understanding of the pandemic's impact and the broader challenges faced by these families, informing future policies and practices to better support them.

The analysis of caregiver experiences during the COVID-19 pandemic has highlighted the profound challenges encountered by those caring for children with ASD. These challenges were multifaceted, touching on every aspect of daily life and significantly impacting the well-being of both children and their caregivers. Disruptions in therapy and education emerged as central concerns, with the abrupt shift to virtual platforms often proving inadequate for the needs of children with ASD. These disruptions hindered the children's developmental progress and placed additional stress on caregivers, who had to navigate new and often less effective modalities of support.

Following the focused examination on ASD within caregiver narratives, a directed content analysis illuminated pressing issues through the lens of the CFIR constructs. This analytical approach facilitated a structured exploration of the broader contextual and systemic factors influencing the experiences of families with ASD. Subsequently, thematic analysis refined these insights, revealing three predominant themes:

1. Disrupted Routines and Therapeutic Interventions
2. Navigating Social Dynamics and Public Perception
3. Mental Health and Access to Services

The integration of CFIR constructs into this exploration offers a framework to understand the multifaceted dimensions of these challenges. By identifying relevant CFIR domains—such as the outer and inner setting, the characteristics of individuals, and the process of implementation—the complexities underlying the provision and reception of support for the ASD community are appreciated. This dual-layered analytical process illuminates the systemic barriers, societal attitudes, and the critical gaps in resources and services that have been magnified by the pandemic. The next sections will delve into the

CFIR analysis, structured around these three principal themes, to elucidate the systemic and contextual influences on the experiences of caregivers and their children with ASD. This will be followed by a detailed exploration of each theme derived from the thematic analysis, offering a deep dive into the lived experiences, challenges, and resilience of these families. Through this examination, the realities faced by the ASD community are highlighted, providing a foundation for informed interventions and support mechanisms.

ASD Directed Content Analysis (CFIR)

The thematic analysis of caregivers' experiences with children with ASD during the COVID-19 pandemic can be enriched by considering CFIR constructs, which offer a lens to examine the multifaceted influences on the implementation of needed interventions and services^{120,121}. Comparing the thematic analysis on caregivers of children with ASD during the COVID-19 pandemic to the CFIR framework codes involves mapping the identified themes to CFIR's five major domains and their underlying constructs.

ASD Theme 1: Disrupted Routines and Therapeutic Interventions

- **Outer Setting (Patient Needs and Resources):** This theme aligns with the CFIR's emphasis on understanding the needs and resources of the target population. The pandemic drastically altered what patients and families needed in terms of support, highlighting gaps in resources for children with ASD.
- **Inner Setting (Available Resources):** The disruptions to therapy and daily routines reflect challenges within service provision settings, including schools and healthcare facilities, to adapt and communicate effectively under pandemic constraints.
- **Intervention Characteristics (Adaptability):** The need for flexible and adaptable interventions is evident in the challenges faced by families, suggesting that services must be tailored to meet the dynamic needs of children with ASD, especially during unforeseen circumstances like a pandemic.

ASD Theme 2: Navigating Social Dynamics and Public Perception

- Outer Setting (External Policies and Incentives): This theme connects with how societal norms and policies impact the acceptance and support of individuals with ASD. Public perception and social dynamics influence the willingness of communities to adapt to and accommodate the needs of those with ASD.
- Characteristics of Individuals (Knowledge and Beliefs about the Intervention): Caregivers' experiences in public settings highlights the importance of individual attitudes and knowledge about ASD, affecting the implementation and effectiveness of social support interventions.

ASD Theme 3: Mental Health and Access to Services

- Outer Setting (Patient Needs and Resources): This theme directly relates to the identification of the needs of individuals with ASD for mental health services and how external policies can facilitate or hinder access to these services.
- Inner Setting (Available Resources): The availability of mental health resources and the organization's readiness to provide these services during a crisis reflect on the inner setting's influence on service delivery.

This comparison validates the relevance of CFIR constructs in understanding and addressing the complex challenges revealed by the following thematic analysis, offering pathways for implementing effective strategies to support children with ASD and their families.

ASD Thematic Analysis

Expanding on the framework provided by the CFIR and directed content analysis, the shift to thematic analysis yields a more detailed exploration of the overarching experiences of caregivers of children with ASD. The CFIR constructs provide a structured lens through which the systemic challenges and opportunities for intervention can be understood. Moving from this macro-level perspective, it is essential to delve into the individual themes identified through thematic analysis to capture the real-world experiences faced by these families. This approach allows for a detailed examination of the specific

challenges, strategies, and needs articulated by caregivers, offering a more granular view of their experiences during the COVID-19 pandemic. **Table 3.5** presents a summary word table that overviews the specific themes identified among caregivers of children with ASD. This table consolidates the descriptive definitions and supporting quotes for each theme, providing a structured overview of the key findings from the analysis.

ASD Theme 1: Disrupted Routines and Therapeutic Interventions

This theme highlights the significant disruptions in daily routines and therapeutic services for children with ASD, exacerbated by the pandemic's restrictions. Families faced the cessation or modification of critical in-person therapies to virtual formats, which were often less effective or completely unfeasible for their children. The abrupt shift impacted children's developmental progress, leading to regression in some cases and placing additional stress on caregivers to fill the therapeutic void. Caregivers shared poignant accounts of how the shift from in-person to virtual learning and therapy failed to meet their children's needs, emphasizing the vital role of structured routines and consistent therapeutic support for children with ASD.

Supporting Quotes:

- *"Early intervention was disrupted... Trying to Zoom a therapist to an autistic child... resulted in a lot of self-injurious behaviors."*
- *"He lost his entire speech therapy and still has only gotten it back through school but even then, it's not enough."*
- *"My daughter... lost all her outside therapy. She lost her OT, she lost her PT, and she lost her speech therapy as well."*
- *"Now thank God she is in school, and I can have that aspect of her in school, and as soon as she gets home, home's a safe place, she just explodes."*
- *"She's sprawled on the floor kicking and screaming... 'She's having a meltdown. Will get over it. If you don't like it, don't look.'"*

ASD Theme 2: Navigating Social Dynamics and Public Perception

This theme explores the social challenges and public misperceptions encountered by families with ASD children, especially in public settings. Caregivers expressed the difficulty of managing public outings due to unpredictable behaviors or meltdowns, which were often met with judgment and a lack of empathy from

others. The stigma associated with visible and invisible disabilities further isolated families, making community integration more challenging. Challenges of social integration for ASD children, focusing on caregiver strategies to manage public perceptions and the need for greater societal empathy.

These themes substantiate the complex landscape navigated by caregivers of children with ASD, marked by disrupted routines, therapeutic challenges, and the constant push for societal understanding and support.

These quotes reveal the struggles faced by families in navigating public spaces, dealing with societal judgment, and advocating for acceptance and understanding of their children's differences.

Supporting Quotes:

- *"Bringing her out into a public area now is absolutely terrifying because I know how she melts down."*
- *"It's frustrating... trying to find people that will come and actually do the job they're supposed to do and then stay and have a good relationship with the child."*
- *"You need the hope that extra home help at home with her just for those certain reasons."*
- *"She also needs to be a part of society, and you guys need to be more accepting and more understanding that not everybody is like you."*
- *"They need to be more empathic. Empathy. That's what they need. That's what the world needs."*

ASD Theme 3: Mental Health and Access to Services

This theme explores the profound mental health impacts of the COVID-19 pandemic on children with ASD and the significant barriers their families faced in accessing necessary mental health services. Throughout the pandemic, caregivers reported increased instances of anxiety, regression in social skills, and heightened behavioral challenges in their children. Compounding these difficulties was the struggle to access timely and effective mental health services, exacerbated by long waitlists, limited availability of specialists familiar with ASD, and the inadequacy of virtual therapy sessions for certain children. Increased mental health challenges among ASD children during the pandemic, compounded by significant barriers in accessing timely and effective services. The following quotes from participants highlight the dire need for enhanced mental health support and the obstacles encountered in securing these critical services during an unprecedented global health crisis. These insights reflect the need for mental health support tailored to

individuals with ASD, emphasizing the critical role of accessible services in mitigating the pandemic's impact on this vulnerable population.

Supporting Quotes:

- *"Mental health services... there's a crisis but it was and is still extremely difficult to access... We were on a rollercoaster... the wait lists were months to access any of the services that we needed."*
- *"Getting my son's 504 plan in place was a real challenge... after the pandemic it took even longer... Where's the sense of urgency on getting the help for these kids?"*
- *"I'm lucky very thankful and very grateful that she has wonderful teachers... but I'm still trying to normalize things for her."*
- *"I just want to jump in and add that mental health services... it was and is still extremely difficult to access."*
- *"There needs to be someone other than the principal... taking their time really looking at these requests from these parents because parents know best."*

Table 3.5: ASD Thematic Analysis Summary - key themes from caregiver narratives on ASD challenges and supports during the pandemic.

Theme	CFIR Domain	Definition	Exemplar Quote
1 Disrupted Routines and Therapeutic Interventions	- Outer Setting (Patient Needs & Resources) - Inner Setting (Available Resources) - Intervention Characteristics (Adaptability)	Impact of COVID-19 on therapy and daily routines for children with ASD. - Highlights the significant disruptions in daily routines and therapeutic services for children with ASD, exacerbated by the pandemic's restrictions. - Families faced the cessation or modification of critical in-person therapies to virtual formats, affecting children's developmental progress.	"Early intervention was disrupted... Trying to Zoom a therapist to an autistic child... resulted in a lot of self-injurious behaviors." "He lost his entire speech therapy and still has only gotten it back through school but even then, it's not enough."
2 Navigating Social Dynamics and Public Perception	- Outer Setting (External Policies and Incentives) - Characteristics of Individuals (Knowledge and Beliefs about the Intervention)	Challenges of social integration for ASD children, focusing on caregiver strategies to manage public perceptions. - Explores the social challenges and public misperceptions encountered by families with ASD children, especially in public settings. - Caregivers expressed difficulty managing public outings due to unpredictable behaviors or meltdowns, met with judgment and lack of empathy.	"Bringing her out into a public area now is absolutely terrifying because I know how she melts down." "You need the hope that extra help at home with her just for those certain reasons."
3 Mental Health and Access to Services	- Outer Setting (Patient Needs and Resources) - Inner Setting (Available Resources)	Increased mental health challenges among ASD children, compounded by significant barriers in accessing services. This theme explores the profound mental health impacts on ASD children and the barriers their families faced in accessing mental health services.	"Mental health services... there's a crisis but it was and is still extremely difficult to access... We were on a rollercoaster... the wait lists have been months."

3.4 Discussion

This investigation aimed to understand the multifaceted challenges faced by caregivers of children with high-needs amid the COVID-19 pandemic. This goal included exploring the obstacles in accessing essential health services such as SARS-CoV-2 testing and COVID-19 vaccinations, alongside tackling social and emotional difficulties. The study's partnership with RIPIN facilitated focus groups that directly involved caregivers, offering a platform for them to share their experiences and the challenges they face.

The study's methodological approach was twofold. Initially, it employed directed content analysis grounded in the CFIR to categorize broad thematic areas encompassing service access, mental health, and the social-emotional impacts on both the children with high-needs and their caregivers. This phase laid the groundwork for a better understanding of the general landscape of the challenges these caregivers encounter. The second phase of the study sharpened the focus, delving into more specific themes that emerged from the focus group discussions, particularly those revolving around social and emotional issues. This deeper dive was important in delineating the unique challenges within the caregiver experiences, highlighting specific areas of need that could inform targeted interventions and support mechanisms. Through this phased approach, the study aimed to capture a holistic view of the caregivers' experiences, providing a detailed foundation for understanding the complex interplay of factors affecting families of children with high-needs during the pandemic.

Upon completing the thematic analysis, the study focused in on the ASD community, recognizing the challenges and themes among caregivers of children with ASD. The focus shifted to extract and scrutinize responses specifically related to autism, aiming to uncover the unique needs, challenges, and experiences these families face. This targeted exploration aimed to enhance understanding of autism within the broader context of high-needs, illuminating specific areas where interventions and support could be most impactful. Through detailed examination, the study sought to provide a deeper insight into the caregiving experience for families navigating autism, enriching the thematic analysis findings with focused attention on this

subgroup. Moreover, the pandemic heightened existing anxieties and behavioral issues among children with ASD, further complicating the task of maintaining mental health and accessing essential services. The struggle to secure necessary resources was exacerbated by the pandemic's restrictions, leading to an increased burden on family dynamics. Caregivers found themselves at the forefront of managing not just the social and mental health impacts on their children, but also the overarching challenges posed by limited access to therapies, educational support, and social resources. This highlighted a need better support systems and targeted interventions to address the challenges that these families face.

Each theme was closely aligned with CFIR subconstructs such as Adaptability, Patient Needs & Resources, Available Resources, and Other Personal Attributes. This alignment highlights the importance of adaptable interventions, acknowledging patient needs, ensuring the availability of resources, and recognizing the personal attributes of individuals in implementing effective support for children with high-needs. Based on the barriers identified, strategies from ERIC were considered for overcoming these barriers. These included enhancing adaptability of services, improving access to resources, and tailoring interventions to meet the unique needs of high-need populations, and fostering collaborative community engagement. This could include developing flexible service delivery models, enhancing communication channels between caregivers and service providers, and leveraging community networks to support families with high-needs.

Suggestions for Improvement

1. **Develop Customizable Support Services:** Tailor services to meet the diverse needs of children with high-needs, ensuring adaptability to changing conditions.
2. **Enhance Mental Health Services:** Increase the availability of specialized mental health support for children and caregivers, addressing gaps exacerbated by the pandemic.

Engaging stakeholders, including families, educators, and healthcare providers, in the development and execution of services for children with ASD is crucial for addressing the identified themes effectively.

3. Mitigate Social Isolation: Create programs and interventions to reduce social isolation and support the development of social skills and emotional resilience.

4. Improve Resource and Service Education: Offer education and outreach to caregivers about available services and mental health resources.

5. Address COVID-19 Service Barriers: Streamline access to COVID-19 testing and vaccinations, making accommodations for children with high-needs.

Each suggestion is justified by the identified need for more accessible services, the critical gaps in mental health support, the adverse effects of social isolation, and the specific barriers to accessing COVID-19-related health services. Addressing these areas can significantly improve the well-being and support of children with high-needs and their caregivers.

Limitations & Future Directions

The limitations of this study are related to its qualitative focus group methodology, which, while rich in detailed personal narratives, may not generalize across all caregivers of high-needs children. The geographical limitation to Rhode Island may also restrict the applicability of findings to other regions with different healthcare systems and support structures. The timing of the focus groups, conducted during the COVID-19 pandemic, may have influenced participants' responses, reflecting the heightened stress and challenges of the period.

This work has identified the significant challenges caregivers of high-needs children face, particularly during the COVID-19 pandemic. This foundation opens several avenues for future research and intervention. Key areas include the exploration of digital and telehealth innovations to support continuous care, the expansion of specialized mental health services for both children and caregivers, and the development of community-based programs to reduce isolation. Additionally, examining the educational system's support mechanisms, advocating for policy improvements, conducting longitudinal studies on the pandemic's long-term effects, and focusing on ASD-specific challenges presents valuable directions. These

efforts aim to develop strategies to support the well-being and development of high-needs children and their caregivers, highlighting the need for inclusive and supportive interventions in the post-pandemic landscape.

More specifically, future research directions could aim to broaden the scope of this study by engaging with additional organizations across Rhode Island, particularly those specializing in ASD. Emphasis should be placed on conducting ASD-specific focus groups and interviews that delve into mental health topics, with a special focus on the needs surrounding mental health education and the use of technological resources. Expanding the topics to include suicide prevention and the development of tailored technological interventions could provide valuable insights. Inclusion of perspectives from healthcare providers and organizational leaders would also enrich the understanding of barriers to accessing healthcare services and mental health resources, offering a more holistic view of the challenges and potential solutions for supporting caregivers of high-needs children.

3.5 Conclusion

In conclusion, Chapter 3 presents the multifaceted challenges faced by caregivers of high-needs children in Rhode Island during the COVID-19 pandemic. Through qualitative focus group discussions, the study uncovers barriers in accessing health care, mental health resources, and the social-emotional toll on both caregivers and children. The findings suggest the pandemic's exacerbation of existing vulnerabilities within this community, highlighting the critical need for targeted interventions and support systems. Recommendations for policy and practice emphasize enhancing service adaptability, mental health support, and education on available resources, aiming to mitigate the impact of such crises on vulnerable populations in the future.

3.6 Acknowledgements

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Chapter 4: Aim 2(a)- Characterizing Children with High-Needs Using Statewide Health Information Exchange Data

List of Chapter Acronyms

ADHD = Attention-Deficit/Hyperactivity Disorder
ASD = Autism Spectrum Disorder
EHR = Electronic Health Record
HIE = Health Information Exchange
ID = Intellectual Disabilities
OCD = Obsessive-Compulsive Disorder
ODD = oppositional defiant disorder
PheWAS/PheCode = Phenome Wide Association Studies
PTSD = Post-Traumatic Stress Disorder

Preface

Chapters 4-7 comprises the computational efforts for Aim 2, highlighting the computational core of this dissertation through the analysis of statewide clinical data from Rhode Island. This aim used computational methodologies to extract insights and uncover knowledge on different aspects of children with high-needs with focused attention on Autism Spectrum Disorder (ASD)

This chapter takes a quantitative approach to characterize children with high-needs using Health Information Exchange (HIE) data. The other chapters of Aim 2 then focus in on ASD. This analysis aims to identify the conditions and clinical profiles prevalent among this group in the state, reflective of the children whose caregivers participated in the focus groups of the qualitative study. This ensures a more holistic view of the healthcare landscape these children navigate.

High-needs children encompass a diverse group with varying conditions that require specialized care and support, including physical disabilities, learning and developmental disorders, sensory impairments, intellectual disabilities, emotional and behavioral disorders, chronic health conditions, neurological

disorders, mental health conditions, medically fragile children, and children in foster care or with unstable living situations. Using statewide HIE data, this chapter seeks to quantitatively describe the population of high-needs children in Rhode Island. This effort enriches the understanding from Aim 2(a-c), which focused on Autism Spectrum Disorder (ASD) and broadens the perspective of the high-needs population, offering insight into the scope of caregivers' experiences discussed in Aim 1 (Chapter 3). By integrating this quantitative analysis with the findings from Aims 1 and 2, this chapter sets the stage for a holistic approach to designing and implementing a technological intervention. The use of HIE data enriches the overall understanding of the high-needs population in Rhode Island and reinforces the study's commitment to evidence-based, user-centered intervention development. This approach ensures that the proposed solutions are grounded in real-world experiences and reflect the actual experiences of high-needs children and their caregivers in Rhode Island. This analysis lays the groundwork for integrating qualitative and quantitative findings to develop informed, evidence-based strategies for improving healthcare outcomes for children with special needs and their caregivers.

4.1 Introduction

This study uses statewide Health Information Exchange (HIE) data to quantitatively describe the high-needs children's population in Rhode Island. The objective is to cultivate a better understanding of the diverse and complex healthcare landscape these children navigate. This perspective is important for several reasons:

1. **Comprehensive Population Overview:** By leveraging HIE data, this section aims to provide a detailed demographic and condition-specific profile of high-needs children across Rhode Island. This analysis will illuminate the prevalence and distribution of various conditions, thereby offering a better understanding of the population's healthcare requirements.
2. **Insight into Caregiver Experiences:** The quantitative data drawn from the HIE complements the qualitative insights from Aim 1, which explored the experiences of caregivers through focus groups. Understanding the broader context in which these caregivers operate allows for a more

informed analysis of the challenges and needs they articulate, grounding their experiences in concrete data.

3. **Identification of Service Gaps:** A detailed examination of the high-needs population through HIE data can help identify potential gaps in healthcare services and resources. This is particularly relevant for developing targeted interventions that address the specific needs of this population.
4. **Foundation for Intervention Development:** The inclusion of demographic and condition information forms a critical foundation for the design and proposal of a technological intervention. By understanding the scope and characteristics of the high-needs population, the intervention can be tailored more effectively to meet their diverse needs.
5. **Evidence-based Policy and Program Development:** The insights gained from the HIE data analysis can inform policymakers and healthcare providers about the scale and nature of the needs within this population. This can lead to more effective allocation of resources and the development of programs that directly address the identified needs.

Children with high-needs encompass a diverse group of individuals requiring significant, often multifaceted support due to various complex conditions¹⁻³. These children typically need more intensive medical, educational, or psychological care. Examples of conditions that may qualify a child as having high or special needs include:

1. **Chronic Health Conditions/Medically Fragile Children:** Children with ongoing medical conditions such as diabetes, epilepsy, or cystic fibrosis may require ongoing management strategies including medication, therapy, and regular medical check-ups. Children with chronic respiratory conditions requiring ventilators, severe congenital heart defects, or other life-limiting conditions that necessitate constant medical care and specialized equipment^{325,326}.
2. **Developmental Disorders:** Children diagnosed with intellectual or developmental disabilities (IDD) display impairments in intellectual functioning, such as reasoning and problem-solving, as

well as adaptive behavior, which includes practical, social, and everyday living skills³²⁷. Common examples include Down syndrome and Fragile X syndrome. ASD is another example of a developmental disorder, which affects social interaction and communication. Other developmental disorders include Down syndrome and Rett syndrome. Learning disabilities such as dyslexia, which affects reading and language processing skills, and dyscalculia, which impacts mathematical abilities, are types of learning disorders. Communication disorders are also can have high-needs. These encompass a wide range of issues related to speech and language, such as stuttering, dysarthria, and language processing disorders³²⁸.

3. **Emotional and Behavioral Disorders:** This includes conditions like attention-deficit/hyperactivity disorder (ADHD), oppositional defiant disorder (ODD), and anxiety disorders. Children in foster care or with unstable living situations also often face high-needs due to the trauma of separation, frequent relocations, and the complexities of their emotional, social, and sometimes physical or developmental health⁶².
4. **Mental Health Conditions:** Children requiring intensive mental health services for conditions like depression, anxiety, and more severe psychiatric disorders³²⁹.
5. **Neurological/Neuromuscular Disorders:** Conditions like epilepsy, which may involve seizures, or Tourette syndrome, which is characterized by repetitive movements or unwanted sounds (tics), are included here. Some of these children can also have physical disabilities. This can range from congenital conditions like cerebral palsy or spina bifida to acquired injuries that result in mobility challenges or the need for assistive devices^{330,331}.
6. **Sensory Impairments:** Children with visual or auditory impairments, such as those who are blind, have low vision, are deaf, or have hearing loss, fall under this category^{332,333}.

The term “high-needs” reflects the depth and breadth of care and resources necessary to support these children effectively. Addressing the requirements involves a collaborative approach across various sectors, including healthcare, education, and social services, to ensure coordinated care.

4.2 Methods

HIE Dataset

Rhode Island’s Health Information Exchange (HIE), known as “CurrentCare,” is operated by the Rhode Island Quality Institute (RIQI). RIQI serves as the state-designated Regional Health Information Organization (RHIO) which manages the dissemination of health information across the state. CurrentCare represents a repository of Electronic Health Record (EHR) data, encompassing records from all acute care hospitals in Rhode Island as well as numerous ambulatory and laboratory facilities. This database covers over 540,000 individuals, making it a valuable resource for healthcare research and population health management. For this work, RIQI provided de-identified data from CurrentCare for the period of January 2018 to April 2023, specifically focusing on the pediatric subpopulation. This subset of data is instrumental in offering insights into the demographics and condition-specific information of children with high or special needs across the state. The CurrentCare database serves as a critical source of data, enabling a detailed characterization of the high-needs pediatric population in Rhode Island.

Data Extraction

The diagnostic groups of interest included: (1) Chronic Conditions/Medically Fragile, (2) Developmental Disorders, (3) Emotional & Behavioral Disorders, (4) Mental Health Disorders, (5) Neurological & Neuromuscular Disorders, and (6) Sensory Impairments. Conditions were identified based on a literature review and were selected for inclusion if they were represented by more than 10 cases within the dataset to maintain privacy standards. Given the complexity of medical diagnoses, conditions were grouped as accurately as possible, acknowledging that some conditions may span multiple groups. The list compiled is comprehensive but not exhaustive and is limited to conditions as coded by SNOMED CT and ICD-10-

CM. The condition cohorts were extracted from the entire pediatric dataset, using ICD-9/10-CM and SNOMED CT diagnosis codes that were mapped to Phenome-Wide Association Studies (PheWAS) groupings³³⁴. Specific ICD codes for each group of conditions are documented in the results table corresponding to each high-needs condition³³⁵.

Data Reporting and Visualization

Counts and prevalence rates for each diagnostic grouping were computed and reported. A tree map diagram was created to visualize the distribution of the various conditions within the high-needs pediatric population. Healthcare utilization was inferred from the total number of patient visits, extracted from visit occurrences in the dataset. Additionally, the number of unique medications prescribed provided an estimate of medical complexity. Both the visit and medication data span the lifetime of the database from 2018 to 2023. It is acknowledged that this may include the same medications prescribed under different names or dosages. Further research is necessary to refine the accuracy of medication counts. Nonetheless, this provides an overview of the medical complexity as indicated by the number of medications prescribed per patient. A list of unique patients was established for each broader high-needs diagnostic grouping. For these groups, the mean and median numbers of visits and medications were calculated and compared against the entire pediatric population. Box plots were then generated to compare the average total number of visits and medications across all groupings, offering a visual comparison of healthcare utilization and medical complexity among the various high-needs diagnostic categories. Data analysis and visualizations were performed using Julia (v.1.7.1) and R-statistical software (v.4.1.3)^{336,337}.

4.3 Results

The characterization of high-needs conditions within the pediatric population used the HIE data set, focusing on identifying patterns of prevalence and healthcare utilization. The analysis provided an organized and detailed representation of various conditions categorized by specific diagnostic groupings.

This involved a review and categorization of conditions based on ICD-10-CM and SNOMED CT codes, identifying the prevalence and distribution of various high-needs conditions.

The study analyzed data concerning a total of 19,754 pediatric patients registered within the HIE. This population served as the basis for extracting detailed information on high-needs conditions and assessing the healthcare engagement of these groups. The conditions of interest were divided into six broad diagnostic categories (1) Chronic Conditions/Medically Fragile, (2) Developmental Disorders, (3) Emotional & Behavioral Disorders, (4) Mental Health Disorders, (5) Neurological & Neuromuscular Disorders, and (6) Sensory Impairments.

Table 4.1 displays the count and prevalence of conditions across these groups. For instance, within the Chronic Conditions/Medically Fragile group, Asthma the highest count with 1,631 cases, representing 8.3% of the total pediatric population analyzed. Similarly, in the Developmental Disorders category, ASD was recorded with 455 cases, a prevalence of 2.3%. The table also highlights that Emotional and Behavioral Disorders such as ADHD had a significant presence, with 1,397 cases, making up 7.1% of the pediatric population. In **Table 4.1**, conditions with lower prevalence were reported, which, despite their smaller numbers, indicate populations with significant and specialized care requirements. Chronic Kidney Disease, although representing a relatively small fraction of the pediatric population at 0.1% with 13 cases, requires intensive and ongoing management, often involving regular dialysis and careful monitoring. Similarly, Juvenile Idiopathic Arthritis, found in 19 cases, and Cystic Fibrosis, with 26 cases, both at 0.1% prevalence, necessitate comprehensive care strategies, including medication management, physical therapy, and frequent hospital visits. Sickle Cell Disease, though accounting for only 0.3% of the population with 64 cases, presents complex challenges due to the risk of severe pain episodes and potential complications, requiring a multidisciplinary approach to care. These conditions, while not as common as others within the high-needs pediatric group, exemplify the diversity and complexity of care required by children with special healthcare needs. They emphasize the importance of specialized services and resources, highlighting the necessity for healthcare systems to accommodate a wide spectrum of chronic and complex conditions beyond those with the highest prevalence.

Table 4.1: Count and Prevalence of High-needs Pediatric Conditions Organized by Diagnostic Groups

Total Pediatric Population		19,754	
Condition	ICD-10-CM Code(s)	Count	Prevalence
Chronic Conditions/Medically Fragile			
Asthma	J45.-	1631	8.3%
Congenital Heart Disease	Q20-24	326	1.7%
Cancer	C00-D45*	59	0.3%
Chronic Kidney Disease	N18.-	13	0.1%
Cystic Fibrosis	E84.-	26	0.1%
Diabetes	E10-E11	357	1.8%
Epilepsy	G40.-	315	1.6%
Juvenile Idiopathic Arthritis	M08.-	19	0.1%
Sickle Cell Disease	D57.-	64	0.3%
Total		2524	12.8%
Developmental Disorders			
Autism Spectrum Disorder	F84.-	455	2.3%
Cerebral Palsy	G80.-	78	0.4%
Chromosomal Anomalies	Q87-Q99	190	1.0%
Down Syndrome	Q90.-	38	0.2%
Intellectual Disabilities	F70-F79	188	1.0%
Learning Disorders	F81.-	298	1.5%
Speech Language Disorders	F80.-	185	0.9%
Tics/Stuttering	F95.-; F98.4; F98.5	793	4.0%
Total		1628	8.2%
Emotional and Behavioral Disorders			
Attention-Deficit/Hyperactivity Disorder (ADHD)	F90.-	1397	7.1%
Adjustment Reaction	F43.-; F94.8	1018	5.2%
Conduct Disorders	F91.-	657	3.3%
Oppositional Defiant Disorder (ODD)	F91.3	150	0.8%
Total		2309	11.7%
Mental Health Disorders			
Anorexia Nervosa	F50.0	32	0.2%
Anxiety	F41.-; F48.-; F99	2034	10.3%
Bipolar Disorder	F31.-	37	0.2%
Bulimia Nervosa	F50.2	16	0.1%
Depression	F32-F33	918	4.6%
Obsessive-Compulsive Disorder (OCD)	F42.-	97	0.5%
Post-Traumatic Stress Disorder (PTSD)	F43.1	321	1.6%
Panic Disorder	F41.0	154	0.8%
Social Anxiety Disorder	F40.1	132	0.7%
Selective Mutism	F94.0	17	0.1%
Total		2195	11.1%
Neurological/Neuromuscular Disorders			
Genetic Disorders: Prader-Willi; Angelman; Charcot-Marie-Tooth; Huntington's; Duchene Muscular Dystrophy	Q87.1; Q93.5; G60.0; G10; G71.0	44	0.2%
Congenital Osteodystrophies	M89.-; Q77-Q78	41	0.2%
Epilepsy	G40.-	315	1.6%
Hemiplegia	G81.-	30	0.2%
Myoneural Disorders/Myopathy	G70.-; G73.-	27	0.1%
Neurofibromatosis	Q85.0	14	0.1%
Torsion Dystonia	G24.-; G80.3	16	0.1%
Total		464	2.3%
Sensory Impairments			
Hearing Loss	H90.-	328	1.7%
Visual Impairments	H54.-	56	0.3%
Total		375	1.9%

Distribution of High-Needs Conditions in Pediatric Population

■ Mental Health Disorders ■ Emotional & Behavioral Disorders ■ Chronic Conditions ■ Developmental Delays ■ Neurological Disorders ■ Sensory Impairments

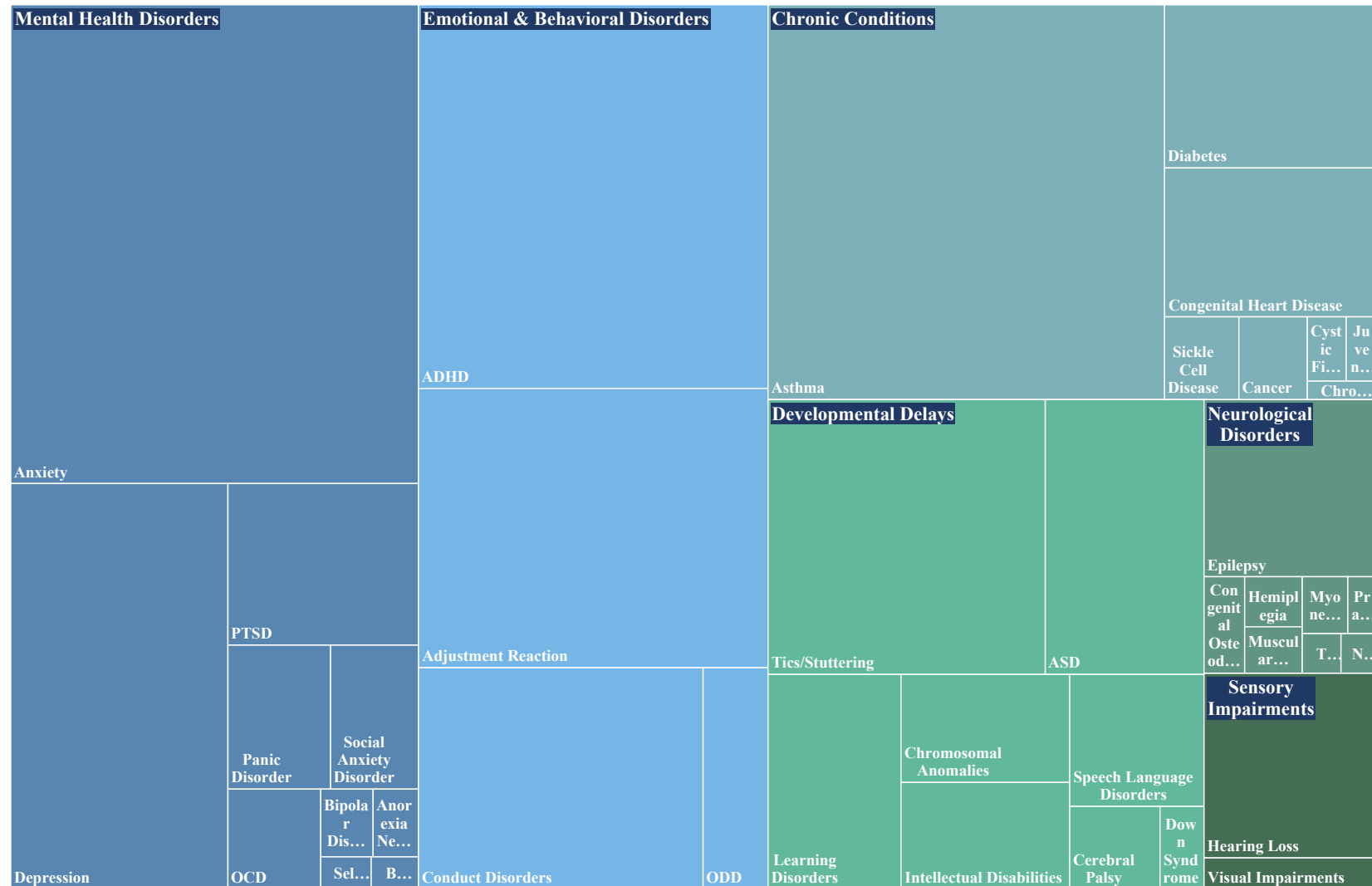


Figure 4.1: Tree Map of High-needs Pediatric Conditions Distribution by Diagnostic Group

Figure 4.1 presents a tree map that graphically represents the distribution of high-needs conditions within the pediatric population based on the diagnostic groupings. The tree map provides a visual differentiation of the prevalence of each condition, allowing for an at-a-glance comparison of the relative sizes of each diagnostic category within the high-needs population. This visualization offers a clear and immediate understanding of how different conditions are proportionally represented within the high-needs population, emphasizing the relative scale of each condition group.

Table 4.2 and **Figure 4.2** show healthcare utilization of the high-needs population, focusing on the number of visits and medications as proxies for medical complexity and healthcare engagement. For instance, the Neurological/Neuromuscular Disorders group demonstrated the highest mean number of visits per patient at 74.8 and a median of 47 visits, indicating substantial healthcare engagement. In terms of medication needs, this group also had the highest mean, with 20.4 unique medications and a median of 17, signifying a complex medical management scenario. The average and median number of medications were similar across the high-needs groups, suggesting a comparable level of medical complexity within these categories. High standard deviations in both visits and medication numbers suggest significant variability within these groups. For example, children with chronic conditions have a mean of 48.8 visits but a standard deviation of 59.3, highlighting wide differences in individual healthcare needs and service utilization. The large standard deviation points to a difference in the extent of healthcare services used among these individuals, but when considering the elevated mean compared to the general pediatric population, it still indicates that children with high-needs have higher healthcare utilization overall. This could be influenced by varying severity of the condition, differences in access to healthcare, or differing treatment approaches among healthcare providers.

These healthcare utilization metrics are visualized in **Figure 4.2** through box plots. Box plots offer a visual summary of the distribution and variation of healthcare utilization metrics across high-needs pediatric groups. Specifically: **Figure 4.2.1** illustrates the distribution and variation of the total number of visits per patient over a 5-year period. The median number of visits is indicated by a line within each box, while the mean is denoted by a “+” symbol. From the box plot, it is evident that all diagnostic groupings

experienced a higher number of visits compared to the overall pediatric population. Notably, the Neurological and Neuromuscular Disorders group had the highest average number of visits, indicating a substantial level of healthcare engagement for these patients. **Figure 4.2.2** showcases the number of medications per patient, with each high-needs group showing a greater number of medications when compared to the general pediatric population. The box plots serve as a tool for conveying the healthcare utilization patterns that distinguish high-needs children from the broader pediatric cohort. These visual representations highlight the unique healthcare demands of the high-needs pediatric groups, reflecting the intensive medical care and management required by these populations.

Table 4.2: *Healthcare Utilization and Medication Needs Among High-Needs Pediatric Groups*

Children with High-Needs Diagnostic Group	Number of Visits		Number of Visits	Number of Medications		Number of Medications
	Mean	(SD)		Mean	(SD)	
All Pediatric Population	25.1	(30.1)	17	11.1	(10.1)	8
Chronic Conditions	48.8	(59.3)	31	19.5	(13.6)	17
Developmental Delays	51	(56.7)	33	18.2	(13.3)	15
Emotional and Behavioral Disorders	41.1	(45.1)	29	18.2	(12.9)	15
Mental Health Disorders	40.1	(41.2)	29	17.8	(12.8)	15
Neurological/Neuromuscular Disorders	74.8	(79.1)	47	20.4	(15.6)	17
Sensory Impairments	65.3	(75.5)	39	20.2	(15.3)	17

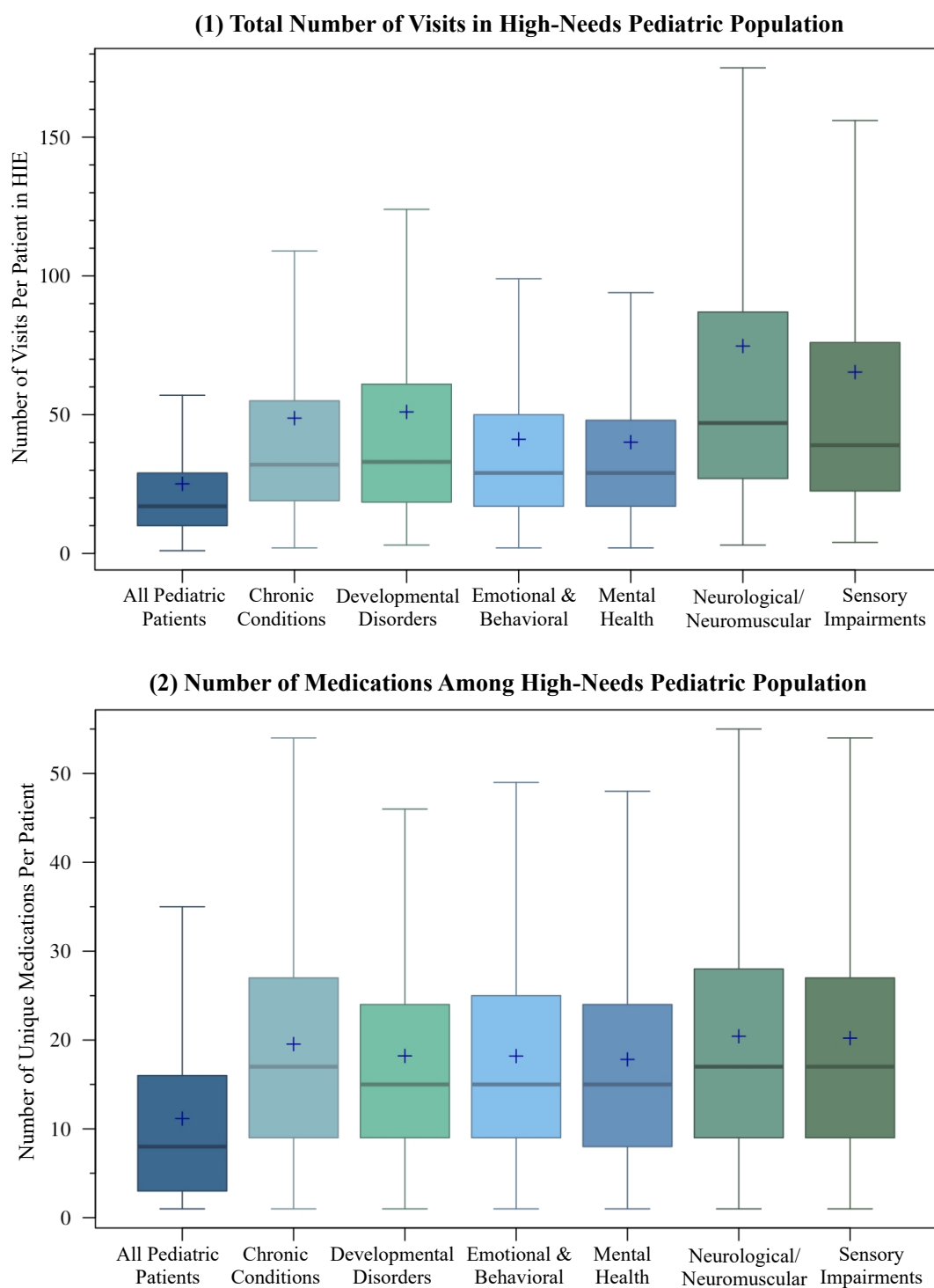


Figure 4.2: Box plots illustrating the distribution of the (1) total number of visits and (2) number of unique medications among high-needs pediatric population.
 (“+” = mean; Outliers removed)

4.4 Discussion

This characterization study offers a vital understanding of the high-needs population in the state of Rhode Island. The analysis of the high-needs pediatric population using HIE data provides a quantitative backdrop to the qualitative narratives obtained from caregivers through focus groups covered in Aim 1. It is important to acknowledge that while the analysis provides an overview of high-needs conditions within the pediatric population, it does not represent an exhaustive list of all possible conditions. The conditions identified and characterized through the HIE data offer a broad understanding of the challenges faced by these children, which is an important aspect to gain context and understanding for what caregivers associated with RIPIN from Aim 1 may be facing. The qualitative insights from these discussions gain depth when contextualized against the backdrop of the diverse and complex conditions outlined in the study.

Furthermore, it is important to note that some of the conditions included in the analysis, such as Asthma or ADHD, might not always signify severe high-needs or special needs in isolation. However, in the context of this study, they are considered within the broader spectrum of high-needs conditions due to their potential to compound other challenges a child faces. For instance, a child with a primary diagnosis that significantly impacts their daily functioning might also have asthma or ADHD, which can exacerbate their overall condition and care complexity. Therefore, these conditions were included in the analysis to reflect a more comprehensive picture of the pediatric high-needs population. This approach to characterizing the high-needs pediatric population demonstrates the complexity of healthcare needs among these children and highlights the importance of considering a wide range of conditions when analyzing caregiver discussions. By doing so, the study acknowledges the multifaceted nature of high-needs and special needs within the pediatric population, providing a more complete understanding that informs the development of targeted interventions and supports. This consideration guides the next steps in Aim 3 of the BD-LHS framework, ensuring that the proposed technological intervention is grounded in a thorough comprehension of the varied and often interrelated challenges faced by high-needs children and their families.

The data elucidated in **Table 4.1**, which includes conditions with lower prevalence rates, sheds light on the challenges faced by this segment of the population, especially during the COVID-19 pandemic and beyond. These conditions, while less common, are characterized by significant healthcare needs that were particularly exacerbated during the pandemic. The quantitative data validates the qualitative accounts of social and emotional impacts reported by caregivers and deepens the understanding of the challenges they face. For instance, conditions such as cystic fibrosis or juvenile arthritis, although not highly prevalent, require intensive, specialized care that likely became more complicated during the pandemic due to issues such as access to care, treatment continuity, and increased risk of COVID-19 complications. The visualization of healthcare utilization in **Figures 4.2.1** and **4.2.2** further illuminate the heightened medical complexity within this group. The Neurological and Neuromuscular Disorders group, for example, showed the highest average number of visits, reflecting the substantial healthcare demands and the potential for disruption during periods of healthcare strain like the pandemic.

4.5 Conclusion

In summary, this study used statewide HIE data to describe children with high-needs in Rhode Island. By categorizing high-needs conditions into broader diagnostic groups, the research provided detailed insights into the prevalence and distribution of various health challenges faced by these individuals. The findings highlight the complexity of healthcare needs within this population, spanning chronic health issues, developmental disorders, emotional and behavioral disorders, mental health conditions, neurological and neuromuscular disorders, and sensory impairments. The analysis revealed notable prevalence rates of conditions such as asthma, congenital heart disease, diabetes, epilepsy, ASD, intellectual disabilities, ADHD, anxiety, depression, and sensory impairments among high-needs children in Rhode Island. These findings highlight the diverse array of health conditions that contribute to the unmet needs of these individuals and emphasize the importance of tailored interventions to address their unique needs.

By quantitatively characterizing these high-needs conditions, this study provides an overview of the healthcare landscape navigated by high-needs children in Rhode Island. The insights gained from this research can inform the development of evidence-based interventions and policies aimed at improving outcomes for this population. Additionally, the findings underscore the need for coordinated care approaches that address the multifaceted healthcare needs of high-needs children across various sectors, including healthcare, education, and social services.

4.6 Acknowledgements

De-identified data for this analysis were provided by the Rhode Island Department of Health (RIDOH) and the Rhode Island Quality Institute (RIQI), which operates CurrentCare, the RI statewide Health Information Exchange (HIE). Technical support was provided by Michelle Torti, CPHIMS, Senior Manager, Data & Product Support at RIQI. The project described was supported by Institutional Development Award Number U54GM115677 from the National Institute of General Medical Sciences of the National Institutes of Health, which funds Advance Rhode Island - Clinical and Translational Research (Advance RI-CTR). The content is solely the responsibility of the authors and does not necessarily represent the official views of RIDOH, RIQI, and the National Institutes of Health. The work was conducted using computational resources and services provided by the Center for Computation and Visualization at Brown University. De-identified data from CurrentCare were provided by RIQI for the study period January 2018 – April 2023. This dataset contained lab-confirmed, suspected, and possible cases of COVID-19. These cases were demographically matched (on age group, sex, race, and ethnicity) to controls who tested negative or equivocal for COVID-19, at a ratio of 1:2 (cases to controls).

Chapter 5: Aim 2(b)- Mental Health Comorbidity Analysis in Pediatric Patients with Autism Spectrum Disorder Using Rhode Island Medical Claims Data

List of Chapter Acronyms

ADHD = Attention-Deficit/Hyperactivity Disorder
ARM = Association Rule Mining
ASD = Autism Spectrum Disorder
EHR = Electronic Health Record
HealthFacts RI = Rhode Island All-Payer Claims Database
PheWAS/PheCode = Phenome Wide Association Studies
PTSD = Post-Traumatic Stress Disorder
SPM = Sequential Pattern Mining

Preface

A version of this chapter has been previously presented at the 2020 American Medical Informatics Association (AMIA) Symposium and published in the associated conference proceedings³³⁸.

This chapter uses medical claims data to study comorbidities in ASD. Identification of comorbidity subgroups linked with ASD could provide promising insight into learning more about this disorder. This study sought to use the Rhode Island All-Payer Claims Database (HealthFacts RI) to examine mental health conditions linked to ASD. Medical claims data for ASD patients and one or more mental health conditions were analyzed using descriptive statistics, association rule mining (ARM), and sequential pattern mining (SPM). The results indicated that patients with ASD have a higher proportion of mental health diagnoses than the general pediatric population. ARM and SPM methods identified patterns of comorbidities commonly seen among ASD patients. Based on the observed patterns and temporal sequences, suicidal ideation, mood disorders, anxiety, and conduct disorders may need focused attention prospectively. Understanding more about groupings of ASD patients and their comorbidity burden can help bridge gaps in knowledge and make strides toward improved outcomes for patients with ASD.

5.1 Introduction

ASD is a group of complex behavioral and developmental disorders that have a broad range of clinical presentations including communication barriers, social-emotional deficits, hyperactivity, hypoactivity, and repetitive movements⁴. While ASD prevalence continues to rise, there is still much unknown about this disorder. Epidemiological evidence indicates that certain medical conditions are more prevalent in children with ASD compared to children in the general population, which makes the study of comorbidities an important focus in the field⁹. Recent efforts have focused on identifying and characterizing subgroup patterns of ASD comorbidities. In several studies, common comorbidity profiles or subgroups that are linked with ASD include seizures, attention deficit hyperactivity disorder (ADHD), gastrointestinal disorders and other psychiatric disorders^{7,9–12,14,15}. A few recent articles have identified that co-occurring psychiatric and medical conditions with ASD account for a substantial burden, and further research and attention is needed in this area for better understanding of the effects of these comorbidities on patient outcomes and direction for overall treatment^{16,339}. Being able to effectively subcategorize patients with ASD based on comorbidity patterns may have broad implications. A characterization of disease development trajectory can facilitate prognosis, inform treatment decisions, and assist in risk stratification for future complications and safety concerns. Categorizing a heterogeneous patient cohort into more homogeneous subgroups is also the first step toward more powerful genomic and molecular studies that can lead toward a better understanding of the etiologies involved in ASD¹⁷¹.

Previous studies have indicated that children with ASD are at an increased risk for being diagnosed with one or more co-occurring mental health conditions^{10,16}, but not much is known about the unique relationships and patterns of the different mental health comorbidities along with the unique trajectories and outcomes of these patients. Research focusing on the treatment and understanding of mental health comorbidities associated with ASD patients has been limited¹⁶. Due to overlapping symptoms and diagnostic bias or interpretation, assessment and prognosis can be extremely challenging and complex. Unsupervised learning approaches such as association rule mining (ARM) and sequential pattern mining

(SPM) can be used as a preliminary analysis to ascertain similarities and temporal patterns for ASD patients diagnosed with one or more mental health disorders.

Data mining methods can be used to link comorbidities and identify unknown patterns to gain knowledge and understanding about the disorder. ARM is a well-established method to discover and identify unique relationships in a dataset. SPM uses longitudinal data to identify temporal or ordered patterns in a dataset³⁴⁰. In this study, ARM and SPM were used to find unique associations between different combinations of mental health disorders in ASD patients compared to the general pediatric population. Combining these two methods can help identify common mental health diagnoses and combinations of diagnoses seen in ASD patients. Taking an unsupervised approach throughout is preferred to minimize clinician label bias with the goal of uncovering unknown patterns and relationships. Although this study does not present new methods, this work presents a new framework on combining different machine learning techniques used in a variety of fields to find patterns and relationships between mental health comorbidity patterns in patients with ASD from a large dataset with limited previous research.

This study sought to use the All-Payer Claims Database in Rhode Island to better understand mental health conditions linked to ASD. The goal of this study was two-fold. First, this study aimed to identify and validate common mental health conditions seen from patients with ASD by using medical claims data in the state of Rhode Island^{341–346}. Most research thus far has only been preliminary with little validation from disparate data sources. By using a large set of medical claims data, trends within the ASD population can be tracked and visualized. The diagnosis rates within a large medical claims dataset can further validate common mental health comorbidities seen in the ASD population. The second aim of this study was to further analyze and identify patterns of ASD patients also diagnosed with mental health conditions using ARM and SPM. Further analysis is needed to determine the importance of the subgroups and infer similarities and relationships.

5.2 Methods

Overview

This study used data from the Rhode Island All-Payer Claims Database (or HealthFacts RI). All analyses were performed using Julia Version 1.3 and R-statistical software Version 3.6.1. All the data were preprocessed in a secure computing environment at Brown University.

Dataset

HealthFacts RI is a de-identified dataset with data beginning in 2011, which includes information from healthcare claims, insurance enrollment information, provider information and other data from Medicare, Medicaid, and large commercial insurance companies (**Figure 5.1**). This dataset is publicly available and is monitored and run by the State of Rhode Island Department of Health. It comprises over 300 million medical claims and includes insurance claim information for over 1 million patients, which is most of the insured Rhode Island residents.

The database consists of solely structured data from medical claims, and the sole features of interest for this project included patient's internal member ID, age, gender, and all associated diagnoses for each patient. In this study, ASD patient cases were extracted from the database using MySQL queries by joining different tables of the HealthFacts RI database and extracting each patient's diagnosis codes reported as International Classification of Diseases, Ninth and Tenth Revision (ICD-9-CM and ICD-10-CM) codes. Two sets of data were extracted. One dataset with all pediatric patients ages 2-21 and another with all pediatric patients ages 2-21 with a diagnosis of ASD (ICD-9/10-CM: 299*/ F84*). The data extracted included information from the entire lifetime of the database (2011-2018). The ages were chosen because these are the time points at which ASD is most likely to be detected. Ages 18-21 were included as most pediatricians can see patients up to 21 years old, and it also includes development of mental health trajectories into the young adult years.

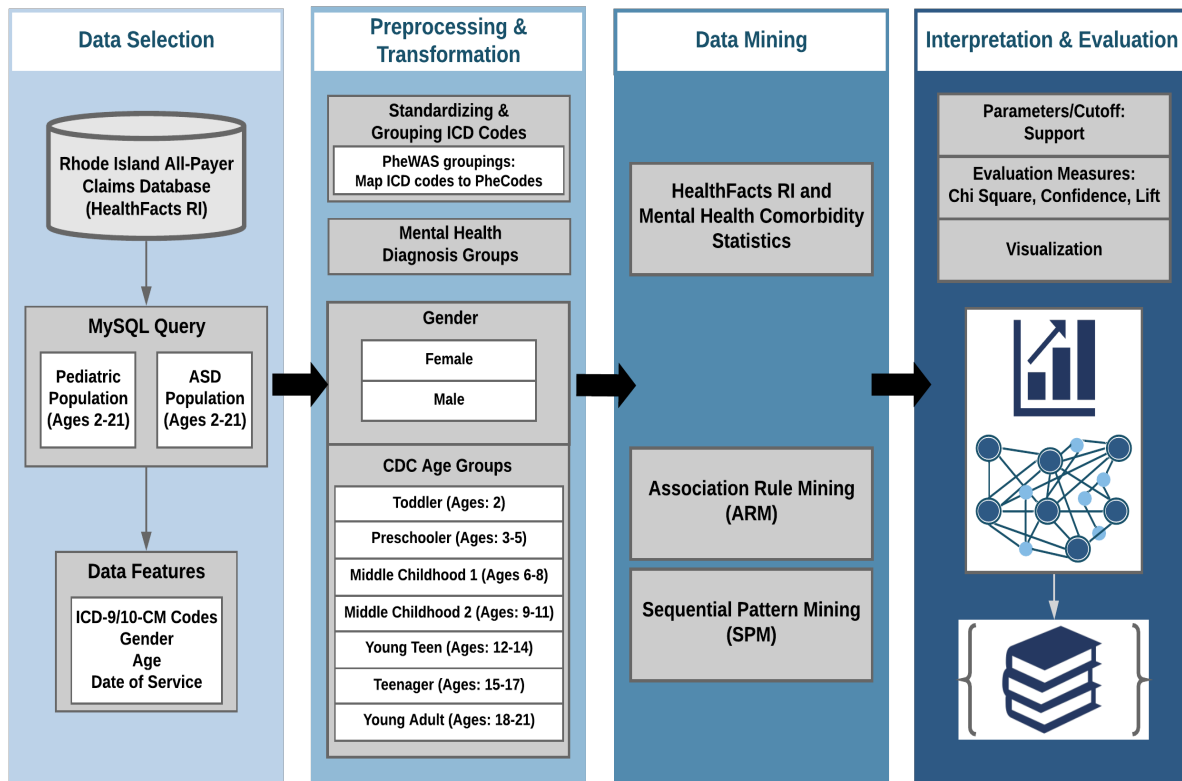


Figure 5.1: Overview of Study Approach

Mental Health Comorbidity Analysis

The data were pre-processed to aggregate various comorbidities into major categories using Phenome Wide Association Studies (PheWAS) categories called PheCodes³³⁴. The dataset consists of all unique patients and their associative PheCode categories. **Table 5.1** shows an example of ICD diagnosis codes mapped to their correlative PheCode group.

The initial MySQL query included all diagnoses for each patient. The PheCodes were filtered to only include all the mental health diagnoses diagnosed for each patient in the dataset. This was done for both the entire pediatric population (ages 2-21) and for the dataset with only patients diagnosed with ASD (ages 2-21). Subsets of the ASD patient population were also separated to take a closer look at gender (male, female) and age groups (toddler (2), preschooler (3-5), middle childhood 1 (6-8), middle childhood 2 (9-11), young teen (12-14), teenager (15-17), and young adult (18-21)). The age groups were determined based on the CDC definition of age groups³⁴⁷. Mental health diagnoses and PheCodes were chosen based on a review article by Rosen *et al.* that identifies the different mental health diagnoses groups with a call to action that more research is needed to understand the risk and treatment for individuals diagnosed with ASD. These included: anxiety disorders, depressive disorders, bipolar disorder, externalizing/ behavior disorders, oppositional defiant disorder/ conduct disorder, schizophrenia/ psychotic disorders, and ADHD as well as a section with other co-occurring conditions (e.g., post-traumatic stress disorder [PTSD])¹⁶. **Table 5.2** describes the 38 PheWAS groups included for analysis in this study.

Table 5.1: Example of ICD-9/10-CM diagnosis billing codes linked to a PheWAS group for depression.

PheWAS Mapping from ICD-9/10-CM to PheCode Example			
ICD-9-CM	ICD-10-CM	PheCode	Phenotype
311,296.36,296.35,296.34,296.33,296.32,296.31,296.3,296.3,296.26,296.25,296.24,296.23,296.22,296.21,296.2,296.2	F33.9,F32.4,F33,F32.5,F32.81,F32.8,F33.8,F33.1,F32.1,F33.0,F32.3,F33.41,F33.3,F33.4,F32.2,F32.9,F33.42,F32.0,F32,F33.40,F33.2,F32.89	296.2,296.22	Depression/ Major Depressive Disorder

Table 5.2: Mental health diagnoses PheWAS groups included in study.

PheCode	Phenotype	PheCode	Phenotype	PheCode	Phenotype
295.0	Schizophrenia and other psychotic disorders	300.11	Generalized anxiety disorder	305.2	Eating disorder
295.1	Schizophrenia	300.12	Agoraphobia; social phobia; and panic disorder	306.0	Other mental disorder
295.2	Paranoid disorders	300.13	Phobia	312.0	Conduct disorders
295.3	Psychosis	300.2	Generalized anxiety & phobic disorders	312.3	Impulse control disorder
296.0	Mood disorders	300.3	Obsessive-compulsive disorder	313.1	Attention-deficit/hyperactivity disorder (ADHD)
296.1	Bipolar	300.4	Dysthymic disorder	313.3	Autism
296.2	Depression	300.8	Acute reaction to stress	315.0	Developmental delays and disorders
296.22	Major depressive disorder	300.9	Posttraumatic stress disorder	315.1	Learning disorder
297.0	Suicidal ideation or attempt	301.0	Personality disorders	315.2	Speech and language disorders
297.1	Suicidal ideation	302.0	Sexual and gender identity disorders	315.3	Mental retardation
297.2	Suicide or self-injury	303.3	Psychogenic disorder	316.0	Substance addiction and disorders
300.0	Anxiety; phobic and dissociative disorder	303.4	Somatoform disorder	317.0	Alcohol-related disorders
300.1	Anxiety disorder	304.0	Adjustment reaction		

Association Rule Mining

ARM is a data mining technique that can be useful for determining relationships between data elements through analysis of patterns in frequent itemsets in the data. This unsupervised learning technique, originally proposed by Aragwal *et al.* in 1993, uses the Apriori algorithm to find a rule or combination of transactions that are related³⁴⁸. The classic example of ARM is the market basket analysis where association rules help uncover relationships of products purchased together at a grocery store. It is used in many other fields including healthcare. Several studies have used ARM to investigate comorbidities among certain patient populations^{349–353}; however, to the best of our knowledge, few studies have comprehensively studied the associations between mental health comorbidities and ASD. ARM uses an efficient algorithm to compute a complete set of frequent itemsets based on a minimum support parameter. An association rule can be visualized as $\{X \rightarrow Y\}$ (or commonly seen as: left hand side {lhs} $\rightarrow$ right hand side {rhs}), which is

the likeliness of finding Y which also has X. An itemset, $\{X,Y\}$, is the list of all items that form the association rule. **Table 5.3** is an example of transactions of mental health comorbidities seen in this study along with two arbitrary examples of returned association rules.

Table 5.3: Examples of mental health diagnoses per patient in dataset (transactions) and arbitrary examples of how the association rules are returned (itemset $\{X,Y\}$ as $\{X \rightarrow Y\}$ rule)

Patient ID	Mental Health Diagnoses (Transactions)
1	ADHD,Anxiety disorder,Depression,Major depressive disorder,Adjustment reaction
2	Learning disorder,Other mental disorder,Speech and language disorder,Mental retardation
3	ADHD,Mental retardation,Mood disorders,Conduct disorders,Anxiety disorder
Example Rule	Association Rules
1	$\{\text{Developmental delays and disorders}, \text{Mood disorders}\} \Rightarrow \{\text{Mental retardation}\}$
2	$\{\text{ADHD}, \text{Anxiety disorder}, \text{Conduct disorders}\} \Rightarrow \{\text{Bipolar}\}$

The support metric gives information on how frequent an itemset occurs in all the transactions. It is the fraction of transactions containing that itemset. Confidence is another metric commonly used to rank and analyze association rules. Confidence is the probability of the occurrence of $\{Y\}$ given that $\{X\}$ is present. A higher confidence means a higher probability that X and Y occur together throughout the dataset. Lift is another metric commonly used to look at the ratio of confidence to baseline probability of occurrence of $\{Y\}$. Lastly, this study also used the chi-square metric for purposes of evaluation and the final determination in statistical significance level of the association rules. Chi-square can be calculated directly from the values of support, confidence and lift³⁵⁴. The chi-square statistic is used to test for independence between the left-hand side and right-hand side of the rule $\{X \rightarrow Y\}$. The null hypothesis is that there is no relationship between the itemsets, and they are independent. A higher chi-square value indicates that the $\{X\}$ and $\{Y\}$ are not independent. The contingency table below shows the relationship between itemsets $\{X,Y\}$ and the formulas for support, confidence, lift, and chi-square (**Table 5.4**).

The ARules and ARulesViz packages were used in Julia and R to run the Apriori algorithm and visualize the top ranked rules³⁵⁵. ARules was run on the All-pediatric patients dataset and then on the ASD dataset. The rules were joined in a table to remove the rules common between the two to leave only the unique rules for ASD. The same process was done for the gender and age groups. The “transactions” entered into the Apriori algorithm were comma separated phenotype descriptions of the PheCodes to run in the package to get an output of ranking rules (**Table 5.3**) A support parameter cutoff of 0.01 was used to include enough transactions in the dataset to be significant but also include diagnoses or combinations of diagnoses that had lower prevalence within the dataset, which could still be important for evaluation. Most commonly, confidence, support, and lift are used as the parameters to rank rules to see which ones are the most similar or meaningful as mentioned above.

Table 5.4: Contingency table for $\{X \rightarrow Y\}$ and associated formulas for measures of interestingness used for ranking and evaluation of the results from ARM and SPM rules.

Support $\{X \rightarrow Y\}$	Lift $\{X \rightarrow Y\}$
$\frac{\text{Trans with both } X \text{ \& } Y}{\text{Total \# of transactions}}$ a	$\frac{\text{confidence}}{\text{trans with } Y / \text{total \# of transactions}}$ $\frac{(a \cdot d - b \cdot c)^2 \cdot (a+b+c+d)}{(a+b) \cdot (c+d) \cdot (b+d) \cdot (a+c)}$
Confidence $\{X \rightarrow Y\}$	Chi-Square (χ^2) $\{X \rightarrow Y\}$
$\frac{\text{Trans with both } X \& Y}{\text{Transactions containing } X}$ $\frac{a}{a+c}$	$n(\text{lift} - 1)^2 \frac{\text{supp conf}}{(\text{conf} - \text{supp})(\text{lift} - \text{conf})}$ $\frac{a \cdot (a+b+c+d)}{(a+b)^2}$

	Y	Y'
X	$n P(X \cap Y) = a$	$n P(X \cap Y') = b$
X'	$n P(X' \cap Y) = c$	$n P(X' \cap Y') = d$

The association rules for each group were ranked and evaluated based on these statistics. Chen *et al.* found that these parameters are not always the best measures to use for ranking as important rules can be missed due to lower occurrence of the certain itemsets³⁵⁶. In the case of medical comorbidities, it is important to not overlook some of the less frequent diagnoses as these can be important, and other more common diagnoses can overshadow interesting patterns. Instead, the chi-square statistic was used as the final parameter to rank the rules and determine statistical significance or importance. ARulesViz was used to generate a visualization of the top rules.

Sequential Pattern Mining

SPM is a data mining technique used to detect ordered patterns within a dataset. It was introduced by Rakesh Agrawal in 1995 as a follow-up to association rule mining, and was originally used in retail to determine the order of items purchased sequentially over time³⁵⁷. Since that time there have been many applications in medicine to help determine risk of health related events with a temporal relationship. Applications are seen in pharmacology, hospital readmissions and comorbidity analyses^{358–364, 32–38}. In one study, Wang *et al.* studied comorbidities commonly seen with Type 2 Diabetes³⁶⁴. There have not been any applications with ASD to the best of our knowledge. The cSPADE (Sequential Pattern Discovery using Equivalence classes) algorithm was used using the R package, aRulesSequences, to get ordered items based on sequence ID (list of patients) and their corresponding items with transaction times, which was the age of the patient when the diagnosis first occurred in the medical claims and the list of mental health diagnoses respectively.

Since the goal of SPM was to identify common temporal or ordered patterns of diagnosis, the dataset was preprocessed to only include the diagnosis on the first time it appeared as an ICD-9/10-CM code in the medical claims dataset. SPM was performed to analyze the data for frequent diagnosis patterns across the entire ASD population. Further work will be done to break down and analyze more granular age and gender groups along with determining if a next diagnosis in a sequence can be accurately predicted based on the ordered data. Similarly, as mentioned above with the ARM analysis, a support parameter cutoff of 0.01 was

used to include enough rules for analysis but still have enough cases within the dataset to be significant. Confidence was used as the measure for ranking the rules and evaluation of significance.

5.3 Results

Some initial descriptive statistics within the dataset were evaluated to examine the diagnosis rates of ASD per year to compare to the CDC national rise in the past decade (2011-2018). As seen in **Figure 5.2**, the rise in diagnosis rates since the inception of the HealthFacts RI database (2011) shows a similar trend to the CDC data. It cannot be compared 1-to-1 because the CDC collects survey data at specific time points and ages,² but the numbers give insight into diagnosis rates within this specific database over time. From the data extracted from HealthFacts RI, there were medical claims data included for a total of 328,378 pediatric patients (ages 2-21), 8,806 ASD patients (ages 2-21), 6,853 males, and 1,976 females. Out of the 8,806 patients with ASD in the dataset, 6,213 (or ~70%) had a mental health diagnosis identified in one of the 38 PheWAS groupings listed in **Table 5.2**. **Table 5.5** includes descriptive statistics for mental health disorders and total patients per gender and age group analyzed using ARM.

Mental Health Comorbidities

Previous studies have shown mental health comorbidities to be more common in patients with a diagnosis of ASD compared to the general pediatric population. The HealthFacts RI database was analyzed to look at the basic statistics of diagnosis rates reported in the dataset. Some phenotypes were grouped together based on similarity of conditions. Most mental health conditions showed higher proportion or percentage within the ASD patient population compared to the general pediatric population (**Figure 5.3**). Out of the initial 38 mental health PheWAS groupings chosen for this study (**Table 5.2**), 14 groups were selected as being most relevant to the ASD population. Some of the groupings were combined (as seen in **Table 5.6** PheCode column), and some were removed based on prevalence (<0.5%) and specificity of the diagnosis grouping. **Table 5.6** describes the groups that showed higher prevalence in the ASD population.

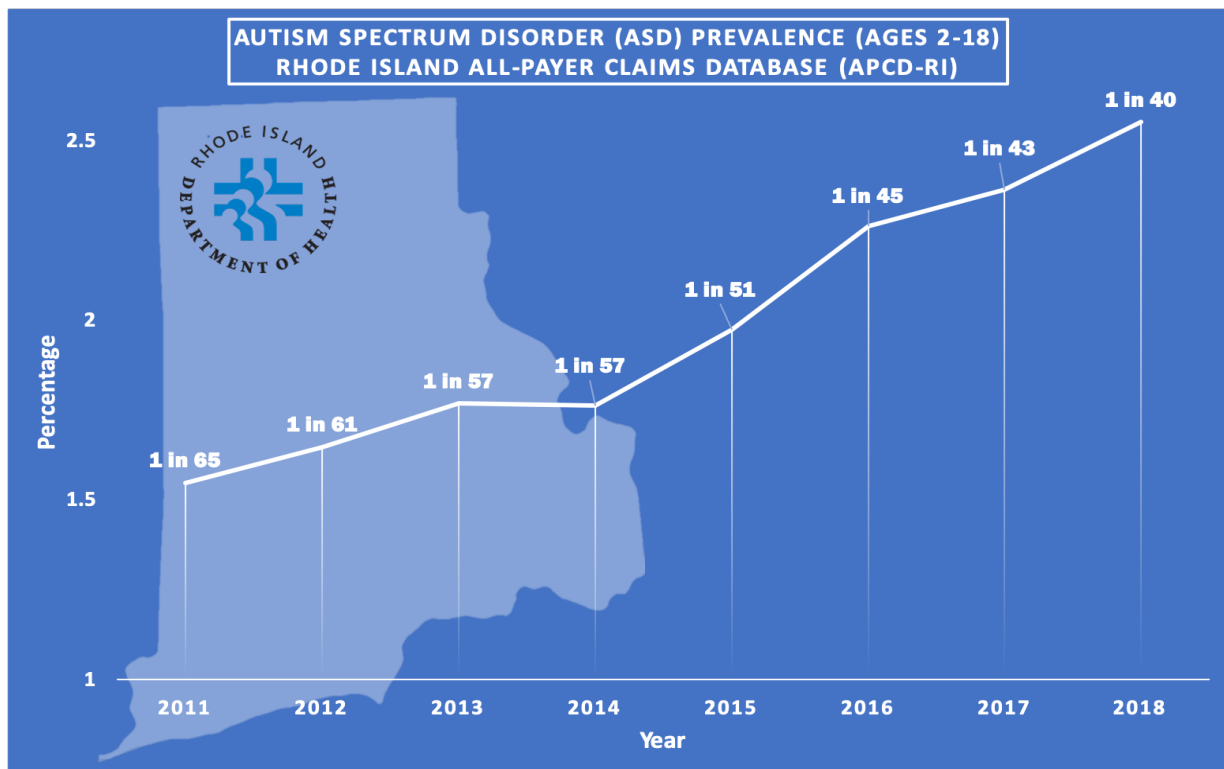


Figure 5.2: Diagnosis rates from HealthFacts RI database

Table 5.5: HealthFacts RI database ASD prevalence by gender and age group

Group	Number	Percentage
Pediatric Patients (2-21)	328,378	--
ASD Total (Ages 2-21)	8806	2.68%
ASD- Mental Health	6213	70.55%
Males	6853	77.82%
Females	1976	22.44%
Toddler	387	4.44%
Preschooler	1138	13.04%
Middle Childhood 1	1418	16.25%
Middle Childhood 2	1634	18.73%
Young Teen	1619	18.56%
Teenager	1425	16.33%
Young Adult	1103	12.64%

Table 5.6: Mental health condition statistics from the HealthFacts RI database for ASD pediatric patients

Mental Health Conditions		Pediatric Population (Total: 328378)		ASD Population (Total: 8806)	
PheCode	Phenotype	Total	Percentage	Total	Percentage
313.1	Attention-deficit/hyperactivity disorder (ADHD)	47110	14.35%	3072	34.89%
300.0, 300.1, 300.11, 300.2	Anxiety disorders	56141	17.10%	2335	26.52%
315.0	Developmental delays and disorders	16187	4.93%	1506	17.10%
315.2	Speech and language disorders	20120	6.13%	1454	16.51%
312.0	Conduct disorders	21221	6.46%	1135	12.89%
296.2, 296.22	Depression/Major Depressive Disorders	35456	10.80%	945	10.73%
296.0	Mood disorders	14652	4.46%	893	10.14%
315.3	Mental retardation	4081	1.24%	683	7.76%
297.0, 297.1, 297.2	Suicidal ideation or attempt/Suicide or self-injury	10575	3.22%	438	4.97%
300.3	Obsessive-compulsive disorder	4075	1.24%	413	4.69%
296.1	Bipolar	6301	1.92%	327	3.71%
300.9	Posttraumatic stress disorder (PTSD)	9085	2.77%	286	3.25%
312.3	Impulse control disorder	2843	0.87%	165	1.87%
295.0, 295.1	Schizophrenia/Psychotic Disorders	1182	0.36%	72	0.82%

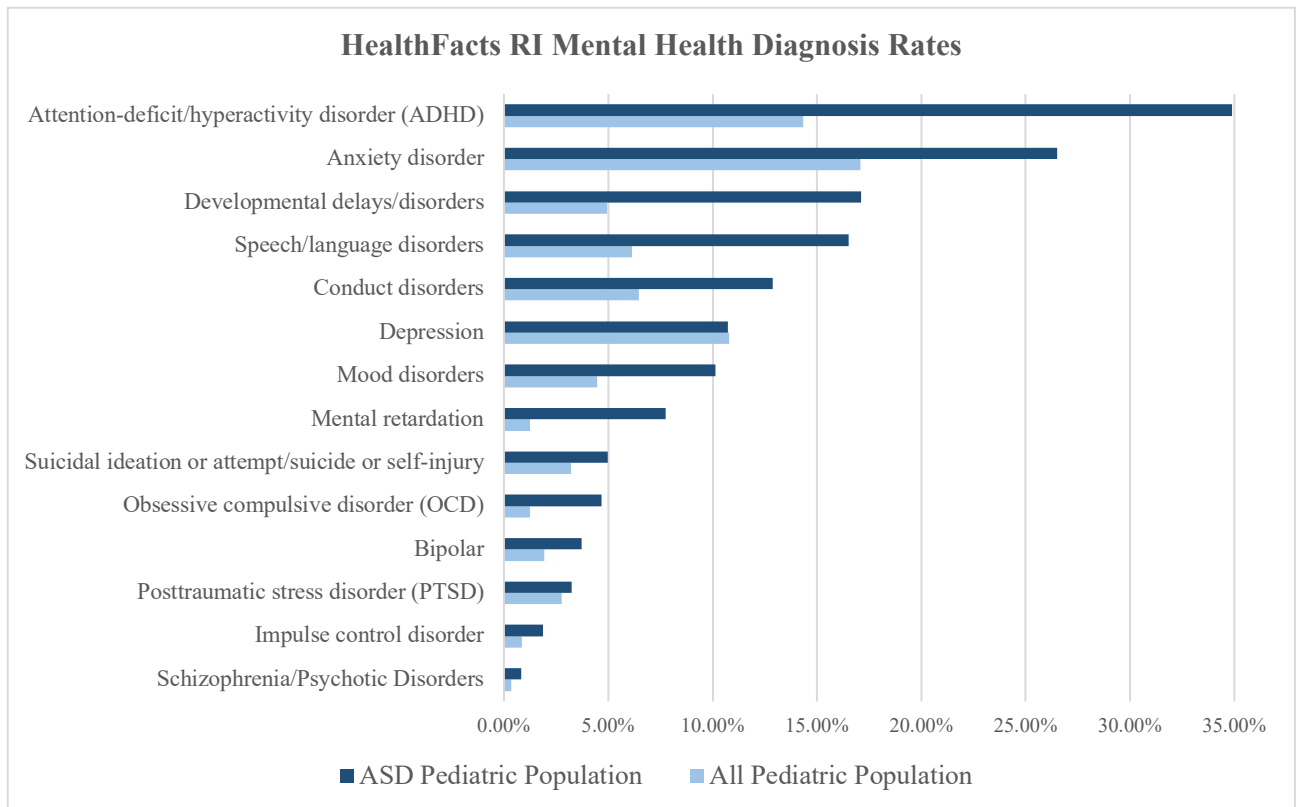


Figure 5.3: *Mental Health Comorbidities – All pediatric population compared to ASD pediatric population.*

Association Rules

ARM was performed on the pediatric population, ASD, gender, and age groups. Included below are the results for several of the top 30 association rules unique to the ASD patient population (**Table 5.7**). ARM analysis showed frequent combinations of anxiety, mood disorders, ADHD, conduct disorders, and suicidal ideation together. This is visualized in the networking diagram shown in **Figure 5.4** of the top 25 rules ranked by chi-square statistic. The combination of disorders seen in the middle of the diagram occur frequently together in this dataset. This initial analysis of mental health conditions is extremely informative for future studies to design algorithms to help predict patients at risk for some of these disorders and the safety concerns associated with them. Anxiety, mood disorders, and conduct disorders is validated in the literature through multiple studies seen in patients with ASD^{7,9-12,14,15}. Suicidal ideation was a diagnosis that was somewhat unexpected. An interesting combination of disorders seen frequently in the dataset included ADHD, anxiety, mood disorders, and conduct disorders (left hand side) often associated with suicidal ideation due to the high chi-square statistic value showing that these are likely not independent of each other. There is little literature available on the risk of suicidal ideation or suicide attempt linked to ASD. Future studies are needed to better understand the risk of suicidal ideation/attempt or self-harm in this patient population and identify interventions that could be specifically tailored for patients with ASD. **Figure 5.5** includes a visualization for the top 30 rules in the male and female ASD groups. The female gender group showed more diagnosis patterns centered around depression, which was not seen in the top rules for the entire ASD population. Other combinations of diagnoses seen in the female group included: anxiety, depression, mood disorders, dysthymic disorder, and suicidal ideation. Ten of the top 30 rules for the male group focused more on conduct disorders, impulse control disorders, and ADHD, but overall contained similar rules to the whole ASD population association rules.

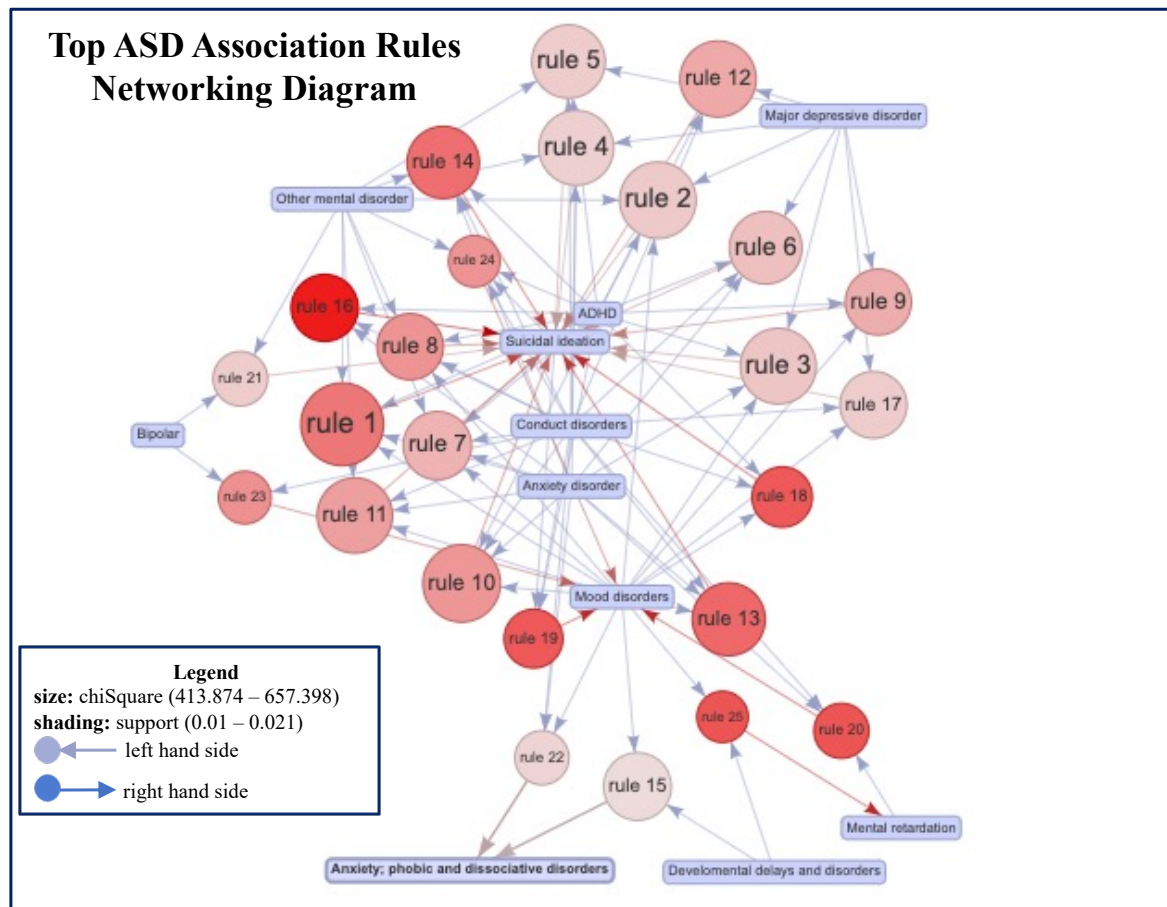


Figure 5.4: Networking diagram of the top 30 association rules for the ASD patient population.

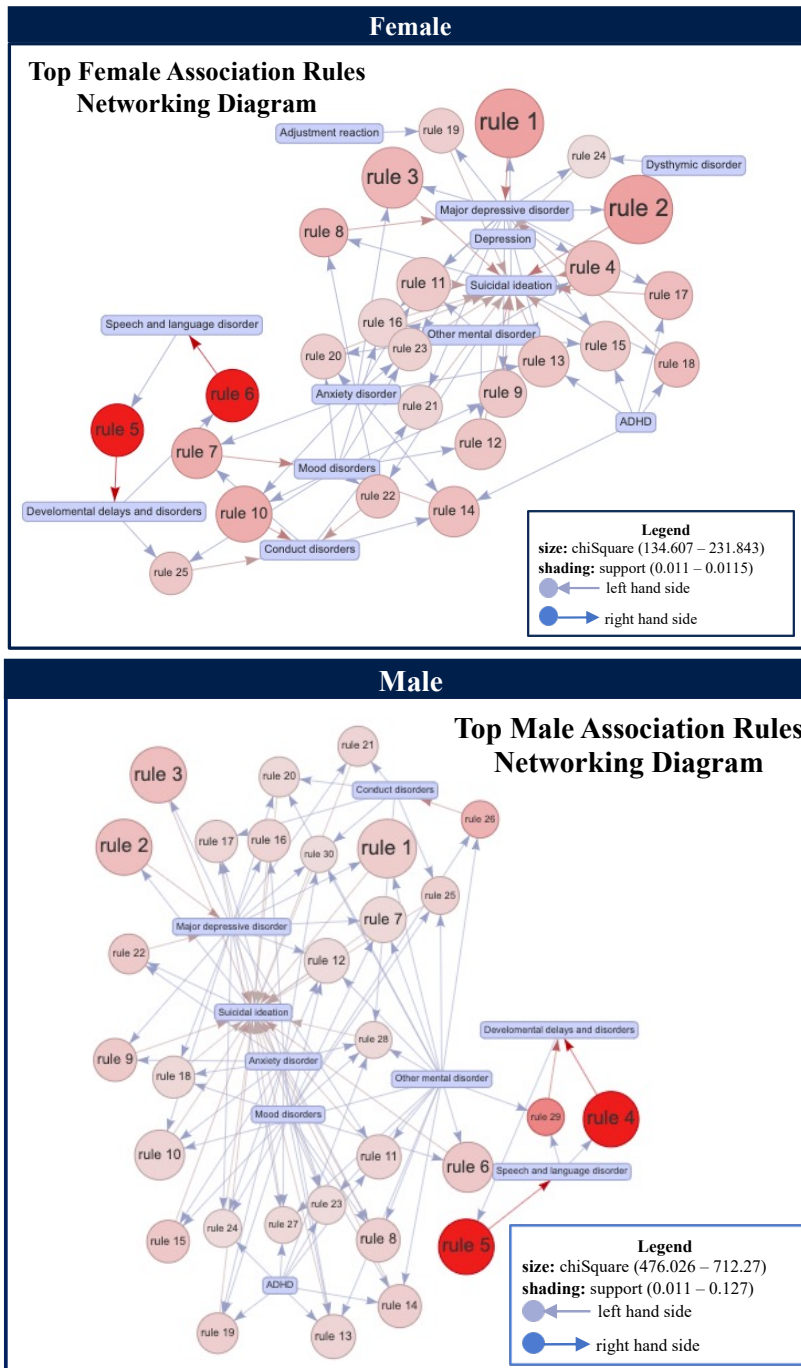


Figure 5.5: Networking diagram of the top 30 association rules for the male and female ASD groups.

Table 5.7: Top association rules for ASD patient population

Association Rules						
Rule	lhs	rhs	chiSquare	p-value(χ^2)	confidence	support
1	{ADHD, Anxiety disorder, Mood disorders, Other mental disorder}	{Suicidal ideation}	657.3981	5.50E-145	0.5096	0.0171
2	{ADHD, Conduct disorders, Mood disorders, Other mental disorder}	{Suicidal ideation}	554.7208	1.18E-122	0.4757	0.0158
3	{ADHD, Anxiety disorder, Conduct disorders, Mood disorders}	{Suicidal ideation}	548.5109	2.65E-121	0.4755	0.0156
5	{ADHD, Anxiety disorder, Conduct disorders, Other mental disorder}	{Suicidal ideation}	520.7474	2.91E-115	0.4202	0.0174
8	{ADHD, Conduct disorders, Suicidal ideation}	{Mood disorders}	452.2976	2.28E-100	0.7355	0.0183
11	{ADHD, Conduct disorders, Other mental disorder, Suicidal ideation}	{Mood disorders}	415.3604	2.50E-92	0.7717	0.0158
12	{Developmental delays and disorders, Mood disorders}	{Mental retardation}	413.8745	5.26E-92	0.5374	0.0185
20	{Anxiety disorder, Mental retardation, Mood disorders}	{Conduct disorders}	358.6943	5.42E-80	0.7770	0.0185
21	{Anxiety disorder, Developmental delays and disorders, Mood disorders}	{Conduct disorders}	356.8445	1.37E-79	0.7971	0.0177
29	{Conduct disorders, Mood disorders}	{Bipolar}	316.2073	9.71E-71	0.2426	0.0159

Sequential Patterns

The top ordered items of SPM rules were analyzed to see sequential analysis of mental health condition diagnosis over time by age of when the first diagnosis appeared within the medical claims ICD-9/10-CM diagnoses (several of the top 50 rules can be seen in **Table 5.8**). The SPM analysis identified ordered sequences of mental health disorders in the dataset. Combinations of different diagnoses commonly showed to result in ADHD included conduct disorders, anxiety disorders, mood disorders, and suicidal ideation in a temporal manner. For example, the top SPM rule indicated that the combination of {Developmental delays and disorders, Speech and language disorder, and Autism} => {ADHD} temporally then resulted in a diagnosis of ADHD with a confidence of 40.5%. Another rule seen with a confidence of 29.3% was {Conduct disorders, Autism} => {ADHD} and {Mood Disorders, Autism} => {ADHD}. This is validated in literature and ADHD is a very common co-occurring diagnosis with ASD^{15,186,352}. A RHS rule of suicidal ideation was observed several times throughout the top 100 SPM rules. As stated with the ARM results, future work is needed to stratify the risk and design predictive models for the risk of suicidal ideation/attempt and self-harm behaviors. These are major safety concerns and limited studies have focused on the correlation between suicide and ASD.

Table 5.8: *Top Sequential Pattern Mining (SPM) rules for ASD patient population*

Sequential Pattern Mining Rules				
Rule	lhs	rhs	confidence	support
1	Developmental delays and disorders, Speech and language disorder, Autism	ADHD	0.40566038	0.01333333
2	Autism	ADHD	0.36491557	0.36186047
3	Mental retardation, Autism	Conduct disorders	0.36082474	0.01085271
4	ADHD, Anxiety disorder, Autism	Conduct disorders	0.33766234	0.01612403
5	Speech and language disorder, Autism	ADHD	0.32231405	0.02418605
6	Developmental delays and disorders, Autism	ADHD	0.3137931	0.02821705
7	Mood disorders, Autism	Conduct disorders	0.30726257	0.01705426
8	Developmental delays and disorders, Autism	Speech and language disorder	0.30344828	0.02728682
9	ADHD, Autism	Anxiety disorder	0.29606299	0.05829457
41	Mood disorders, Autism	Suicidal ideation	0.18994413	0.01054264

5.4 Discussion

Research has indicated that early intervention is key to improving outcomes for patients with ASD. Many research efforts have focused on the early diagnosis of ASD; however, not many studies have focused on studying the progression of the disorder. Studying the comorbidity profiles and characterizing the safety outcomes for patients with ASD is an important focus in the field. Data mining methods leveraging clinical data can be used to identify unknown patterns and characterize the risk factors and outcomes leading to these comorbidities. The progression of ASD is complex and risk stratification, or the development of tools to predict risk for divergent progressions of ASD, is needed to intervene as early as possible and improve outcomes for ASD patients. This study confirmed that mental health comorbidities in children with ASD have a high prevalence, generating concern for patient safety¹⁶. Safety concerns include suicide attempt and aggressive behaviors that lead to harm to self or others. Implementation of clinical interventions using informatics techniques can help improve outcomes for patients with ASD at increased risk for these significant safety concerns.

Analyzing data within a large medical claims database such as HealthFacts RI shows valuable insight into patterns and similarities in the patient population. This database was created to be accessible by providers, state agencies, researchers, and health systems, and insurers to help identify areas to improve healthcare

and reduce costs. Rhode Island is an ideal area to obtain more holistic data due to the wide variety of demographic, social and economic factors within one entire state. The use of medical claims data in healthcare research has shown to have advantages such as large amounts of data, diverse sample sizes, consistent variables, anonymity, and accessibility³⁶⁵. Although challenges exist with medical claims data, the use of ICD-9/10-CM diagnosis codes allow us to gain knowledge about large patient cohorts. Previous literature has identified high rates of mental health disorders in patients that have ASD compared to the general pediatric population. The results from this study validated that for many mental health conditions (PheWAS groupings), there was a higher proportion of diagnoses seen in the ASD population than the general pediatric population. ARM showed interesting combinations of comorbidities related to common outputs (rhs). Based on the observed patterns and temporal sequences, suicidal ideation, mood disorders, anxiety, and conduct disorders may need focused attention prospectively. Understanding more about groupings of ASD patients and their comorbidity burden can help bridge gaps in knowledge and make strides toward improved outcomes for patients with ASD. Rules with large chi-square included combinations of disorders with a highly similar relationship to suicidal ideation as the right-hand side in most rules. This was often missed in the confidence, support, and lift measures due to frequency of the condition in the dataset. This is interesting because the unique combinations of diagnoses linked with suicidal ideation is a safety concern important to focus on in future work.

Medical claim datasets are a rich source of information for a large population. This makes it a great data source to study, but there are also limitations. Medical claims data only shows billing data, and it is well known that ICD-9/10-CM codes have some disadvantages and do not represent the whole picture. For example, there were many patients excluded from the study because the only diagnosis on file was one for ASD. Mental health conditions are often hard to study because much information resides in clinical notes. Due to data incompleteness, future studies will look at other data sources including Electronic Health Record (EHR) data and data from current clinical studies for a cohort of ASD patients. These future studies can consider factors other than diagnosis codes and use techniques such as natural language processing to

better study patients with mental health comorbidities in the ASD population. This study was a preliminary analysis of mental health comorbidities seen in patients diagnosed with ASD. The results indicated that patients with ASD have a higher proportion of mental health diagnoses than the general pediatric population. ARM and SPM methods identified patterns of comorbidities that are commonly seen among ASD patients. Based on the patterns and temporal sequences seen, some disorders that need focused attention in future work include suicidal ideation, mood disorders, anxiety, and conduct disorders. Since it is now well-established that patients with ASD are at a higher risk of being diagnosed with another mental health disorder, other factors can be studied to stratify risk for being diagnosed with specific mental health disorders. Time series analysis and predictive modeling can help determine patients who may be at risk for some of these mental health disorders and help prevent safety concerns such as suicidal ideation and self-harm. Future work will include the use of clustering techniques to subcategorize patients based on their entire comorbidity profile. Additionally, behavioral and mental health clinicians will validate the patterns of mental health comorbidities identified in this study as part of formal evaluations.

5.5 Conclusion

This study aimed to use unsupervised machine learning methods to better characterize patients with ASD, and further expand to specifically characterize patterns and similarities for patients with multiple mental health comorbidities. Using the HealthFacts RI database, structured ICD-9/10-CM codes were extracted to look at correlated conditions across the pediatric patient population. The results indicated that there are common groupings of specific mental health disorders that are seen as unique combinations compared to the general pediatric population. We were able to identify common combinations of clinically accurate mental health conditions seen in patients with ASD. This was also the case for SPM and the order in which these diagnoses first appear by date in the dataset. Further analysis will be done to study some of the interactions of conditions not studied extensively up to this point, along with other medical comorbidities (other than mental health) for this patient population. These results validated current literature and help to

inform future work for the design and development of models and algorithms to help predict trajectories and outcomes for patients with ASD.

5.6 Acknowledgements

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Chapter 6: Aim 2(c)- Data-Driven Insights into Autism Spectrum Disorder and Co-Occurring Conditions: A Cluster Analysis of Health Information Exchange Data

List of Chapter Acronyms

ADHD	= Attention-Deficit/Hyperactivity Disorder
ANN	= Artificial Neural Network
ASD	= Autism Spectrum Disorder
CCSR	= Clinical Classifications Software Refined
CurrentCare	= Rhode Island Quality Institute's Health Information Exchange
EHR	= Electronic Health Record
GI	= Gastrointestinal
HIE	= Health Information Exchange
IDD	= Intellectual and Developmental Disabilities
OCD	= Obsessive-Compulsive Disorder
OHDSI	= Observational Health Data Sciences and Informatics
OMOP	= Observational Medical Outcomes Partnership
PheWAS/PheCode	= Phenome Wide Association Studies
PTSD	= Post-Traumatic Stress Disorder
RIQI	= Rhode Island Quality Institute
SOM	= Self-Organizing Map
STB	= Suicidal Thoughts and Behaviors
WSS	= Within-Cluster Sum of Squares

Preface

A version of this chapter is in preparation as a manuscript for submission.

Continuing the computational exploration within Aim 2, Chapter 6 uses Health Information Exchange (HIE) data to dissect and study the various subgroups within the Autism Spectrum Disorder (ASD) community, enhancing our understanding of the complexity of the disorder. This study investigates the incidence and patterns of co-occurring conditions in individuals with ASD leveraging data from the Rhode Island Quality Institute's Health Information Exchange (CurrentCare). Employing data mining and unsupervised machine learning, specifically Self-Organizing Maps (SOM), the research aims to identify

clusters within the pediatric population based on clinical features and comorbidities. Focusing on ASD patients, the study examines demographic characteristics, healthcare utilization, and the burden of comorbid conditions, particularly mental health disorders. The analysis reveals notable patterns in demographics, diagnoses, and heightened mental health issues within the ASD subgroup. Clustering techniques elucidate groups within the ASD population, each presenting unique comorbidity profiles, thereby underscoring the necessity for personalized care strategies. This research contributes to a deeper understanding of ASD, emphasizing the importance of early intervention and highlights the potential of predictive modeling based on patient profiles and characteristics, aiming to facilitate earlier diagnosis and assess risk for adverse mental health outcomes. It emphasizes the importance of tailored interventions, paving the way for more personalized and effective care strategies for individuals with ASD.

6.1 Introduction

ASD is a developmental disorder marked by difficulties in social interaction, communication, and restricted repetitive behaviors, affecting daily life from early childhood⁴. Literature indicates that individuals with ASD may experience a heightened burden of co-occurring conditions, particularly behavioral and mental health issues. Studies have consistently shown that individuals with ASD are at a higher risk for a range of comorbid conditions^{7,10,338}. These conditions include but are not limited to, attention deficit hyperactivity disorder (ADHD), anxiety disorders, depression, sleep disturbances, and gastrointestinal problems^{9,366}. The heightened burden of these comorbidities can significantly impact the quality of life and can pose challenges for treatment, as they may complicate the clinical picture and the management of ASD. Behavioral issues in ASD may manifest as aggression, self-injury, or severe tantrums, often as a response to the sensory overload or inability to communicate effectively³⁵. Mental health issues often present as anxiety and mood disorders, which can be exacerbated by the core social and communicative challenges of ASD.³⁶⁷ The reasons for the increased prevalence of these comorbid conditions are not fully understood, but it is hypothesized that a combination of genetic, neurobiological, and environmental factors contribute to this phenomenon³⁶⁸. The interactions between these factors are complex and are a current topic of research³⁶⁹.

Early identification and intervention for these comorbid conditions are crucial for improving the overall prognosis and well-being of individuals with ASD^{370,371}. As such, care for those with ASD often requires a multidisciplinary approach that addresses both the core symptoms of ASD and the associated comorbid conditions.

This research aimed to substantiate the hypothesis that individuals diagnosed with ASD demonstrate a significantly higher prevalence of co-occurring conditions, including mental health disorders. By employing advanced clustering techniques, the study endeavors to uncover discernible patterns within these co-occurrences, providing insights into the interplay between ASD and its comorbid conditions. The research aimed to discern key patterns and clinical features within this population by leveraging Health Information Exchange (HIE) pediatric data. The study used data mining techniques to characterize the pediatric dataset and specifically, the subset of individuals with ASD. By applying unsupervised clustering methods—a branch of machine learning—the research intended to group individuals with ASD into clusters based on similar clinical features and comorbidities. This approach facilitated a deeper understanding of the patient profiles within these clusters.

HIE data offer valuable population-level insights. In this study, we leverage the capabilities of the HIE data to investigate ASD the pediatric population. The data accessible through this HIE provide a rich, population-level dataset that ensures a broad and inclusive perspective, critical for the generalizability of our findings. When paired with data mining, it becomes a powerful tool for comprehending the broader community and population, allowing for the identification of outcomes specific to individuals with ASD. The study examined the phenotypic profiles of patients and the burden of comorbidities, which may escalate the risk for mental health issues. Through this data-driven approach, this study aims to uncover patterns of comorbidities and mental health challenges faced by individuals with ASD, with the goal of informing more effective, personalized care strategies.

6.2 Methods

This study, as illustrated in **Figure 6.1**, used statewide de-identified electronic health data to identify individuals with ASD and extract pertinent demographics and clinical diagnoses. This methodological framework was aimed at dissecting the demographic and diagnostic data to discern patterns and associations within the ASD population. Statistical and machine learning analyses were performed using Julia (v.1.7.1) and R-statistical software (v.4.1.3)^{336,337}.

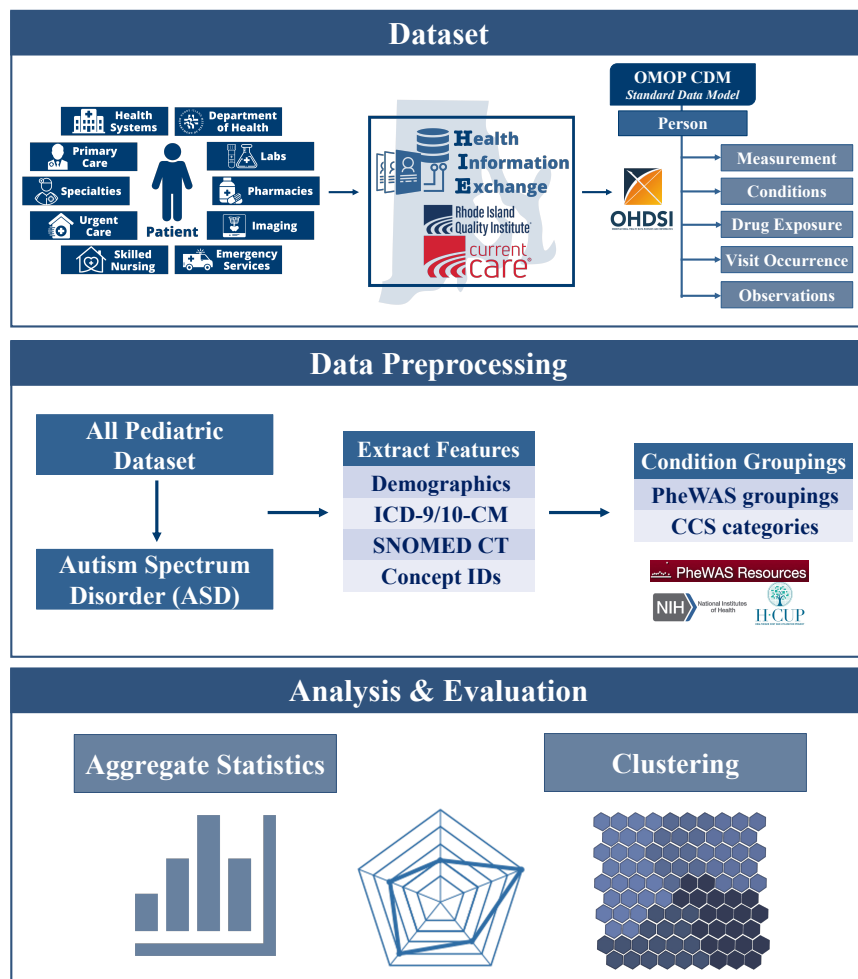


Figure 6.1: Overview of the study

Dataset

The Rhode Island Quality Institute (RIQI) operates Rhode Island's HIE "CurrentCare" and is the state-designated Regional Health Information Organization (RHIO). CurrentCare contains Electronic Health Record (EHR) data from all acute care hospitals in Rhode Island and from many ambulatory and laboratory facilities across the state for over 540,000 individuals. De-identified data from CurrentCare were provided by RIQI for the study period January 2018 – April 2023 limited to the pediatric subpopulation. The de-identification strategy (HIPAA expert determination) included randomly shifting dates, consistently per patient. This dataset adopted the Observational Medical Outcomes Partnership (OMOP) Common Data Model format, leveraged by the Observational Health Data Sciences and Informatics (OHDSI) program.

Data Processing

In this study, the ASD cohort was identified from the entire pediatric dataset using a combination of ICD-9/10-CM, SNOMED CT diagnosis codes, and OMOP Concept IDs as seen in **Table 6.1**^{335,372}. Demographic information including sex, ethnicity, and age range was extracted. Age ranges were systematically computed from the reported year of birth, which was provided in five-year increments due to the de-identified nature of the dataset. The mapping from the year of birth to specific age ranges was determined according to the dataset's extraction point in June 2023. Consequently, individuals born in the year 2020 were categorized within the 0-3 years age group, those born in 2015 fell into the 4-8 years age bracket, births in 2010 were classified as 9-13 years old, and individuals born in 2005 were allocated to the 14-18 years age range. This age classification allowed for the structured examination of developmental stages and their potential impact on the study's outcomes.

The identification of relevant conditions and characteristics was carried out using OMOP Concept IDs, ICD-9/10-CM codes, and SNOMED CT codes. These identifiers were subsequently consolidated into broader categories, using the framework of Phenome Wide Association Studies (PheWAS) to derive "PheCodes" and employing the Clinical Classifications Software Refined (CCSR) for single-level

categorizations^{334,373}. The process included converting SNOMED CT codes into ICD-10-CM codes, following the SNOMED CT to ICD-10-CM Map provided by the National Library of Medicine³⁷⁴. Specifically, mental health disorders such as depression, anxiety, posttraumatic stress disorder (PTSD), acute stress reactions, and psychotic disorders were pinpointed for analysis. Moreover, conditions with high incidence rates, including but not limited to asthma, diabetes, and epilepsy, were categorized and extracted for further study. An illustrative example of the mental health disorder categorization is provided for PTSD in **Table 6.2**, which details the relevant PheCode and CCSR mapping codes for this specific condition. **Appendix B** provides more information on the conditions of interest for this study with corresponding CCSR and PheCodes. Descriptions are provided for some codes to provide more clarity on the broader definitions of different condition groupings.

Table 6.1: ASD cohort defined using ICD-9-CM, ICD-10-CM, SNOMED CT, and OMOP Concept IDs to capture all possible ASD cases.

Terminology	Codes
ICD-9-CM	[299, 299.0, 299.00, 299.01, 299.1, 299.10, 299.11, 299.8, 299.80, 299.81, 299.9, 299.90, 299.91]
ICD-10-CM	[F84, F84.0, F84.3, F84.5, F84.8, F84.9]
SNOMED CT	[35919005, 1925800000, 229710003, 367103007, 442314000, 23560001, 718393002, 231536004, 408856003, 373618009]
OMOP Concept IDs	[439776, 40389260, 40433924, 40546227, 40482738, 4053178, 37397680, 4338037, 439780, 4189466]

Table 6.2: Example of condition groupings for PheCode and CCSR

Grouping	Code	Description	ICD-10-CM Codes
PheCode	300.8	Acute reaction to stress	F43.0, R45.7
	300.9	Post-traumatic stress disorder (PTSD)	F43.12, F43.11, F43.1, F43.10, Z86.51
CCSR Category (single-level)	MBD007	Trauma- and stressor-related disorders	F430, F43.10, F43.11, F43.12, F43.20, F43.21, F43.22, F43.23, F43.24, F43.25, F43.29, F43.8, F43.9, F44.0, F44.1, F44.2, F44.4, F44.5, F44.6, F44.7, F44.81, F44.89, F44.9

The research characterized the study group by conducting a statistical examination and comparison of demographic and diagnostic characteristics, comparing individuals with ASD to other pediatric patients. To assess differences in comorbidities between those with and without ASD, chi-square (X^2) tests were used. The diagnostic codes were organized into single-level categories according to the CCSR creating a detailed binary matrix in a wide format (**Figure 6.3a**). This matrix, used for two unsupervised clustering analysis of the entire population and ASD subgroup, listed unique patients alongside their corresponding CCSR categories, marking the presence of a condition with '1' and its absence with '0'. Categories appearing in less than 0.5% of cases were omitted, leaving 403 (out of 530) categories for the analysis. A Manhattan distance metric was applied to calculate a distance matrix for the binary categorical data, aiding in the cluster analysis.

Clustering - Self-Organizing Map

The Self-Organizing Map (SOM), conceived by Kohonen, is a type of artificial neural network that is used for unsupervised learning and dimensionality reduction^{138,139,375}. It helps organize the data into a lower-dimensional grid or map. This neural network retains the original data's topological features, organizing it into a grid of nodes where similar data points are clustered together. SOMs were used due to their capability in clustering clinical condition data, which is often categorical, binary, and high-dimensional in nature. SOMs are particularly well-suited for such datasets as they can effectively reduce dimensionality and reveal intrinsic patterns in the data without presupposing any distribution, thereby accommodating the complex and heterogeneous characteristics of clinical data. This makes them ideal for identifying groupings and patterns within the clinical conditions under investigation^{376,377}.

In this study, a two-phased approach was adopted to unravel complex data structures within the patient cohort (**Figure 6.3**)^{378–380}. In the initial phase, the patient-level data with CCSR condition groupings as features is fed into the SOM algorithm (**Figure 6.3b**). During training, the SOM learns to map the high-dimensional patient data onto this lower-dimensional grid while preserving the topological relationships between data points. As a result, each node or neuron on the SOM grid represents a cluster prototype, and

similar patients are mapped to nearby neurons on the grid (**Figure 6.2**). The SOM phase helps identify initial cluster groupings based on the CCSR features and their topological relationships. In the second phase, the cluster boundaries are refined using a classic clustering algorithm such as K-means or hierarchical clustering (**Figure 6.3c**)³⁸¹. The initial cluster prototypes generated by the SOM serve as the starting points for the classic clustering algorithm. K-means clustering partitions the data into clusters based on the mean of data points, while hierarchical clustering builds a hierarchy of clusters by successively merging or splitting clusters. These classic clustering algorithms help finalize and refine the patient-level cluster assignments, leading to well-defined and non-overlapping clusters based on condition groupings (CCSR). The choice of the specific classic clustering algorithm may depend on the characteristics of the data and the desired clustering outcome. Overall, this two-phase process combines the strengths of SOM for topological organization and dimensionality reduction with classic clustering algorithms to create meaningful and refined patient-level clusters based on condition groupings. The process commences with the grid nodes being randomly populated with data samples. Through iterative comparison of distances, the algorithm assigns each data point to the nearest node.

The preliminary phase involved generating a SOM with a grid of nodes, providing an overview of the data through "proto-clusters." The determination of the lattice size was driven by the aim to achieve an equitable distribution of patient data across the nodes. For the whole patient dataset, a 53x53 node grid was implemented to accommodate the larger number of individuals, whereas for the subset of patients with ASD, a more compact 20x20 node grid was used, reflecting the smaller size of this specific group. This strategic sizing ensured that the SOM could effectively encapsulate and differentiate the complex patterns inherent within each unique subset of patient data. The SOM underwent training with a variety of parameters, initially with a large learning rate (α) and a narrowly defined width for the neighborhood function. As the process evolved, the SOM parameters were fine-tuned, incrementally amplifying the iterations from 100 to 5000. This careful observation of the learning rate, coupled with the visualization of the map's initial outputs, revealed an optimal configuration at the convergence of lower iterations and a

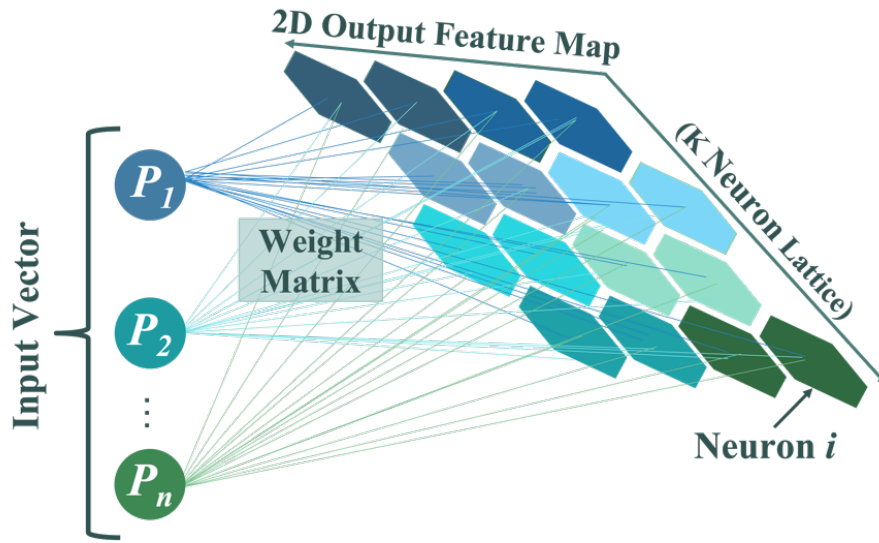


Figure 6.2: Self-organizing map (SOM) artificial neural network (ANN) algorithm produces a two-dimensional grid from the higher-dimensional input matrix. [Figure from Brown et al. (2022)³⁷⁶]

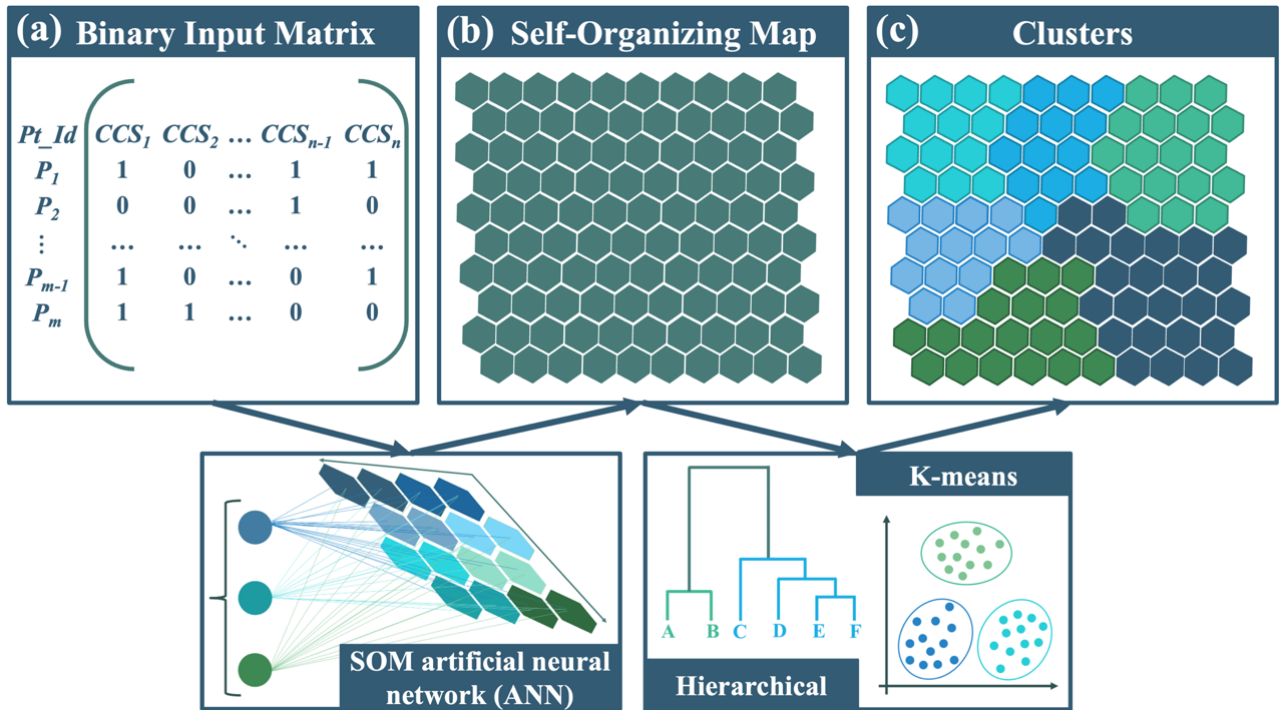


Figure 6.3: Two-Level SOM Clustering Approach: (1) original data projected onto a SOM grid and (2) proto-clusters grouped to form the final clusters [Figure from Brown et al. (2022)³⁷⁶]

reduced learning rate. Such adjustments were key in achieving a more precise SOM by mitigating excessive data convergence, thereby enhancing the quality of the resultant clusters. After the SOM training, the grid was further segmented using clustering algorithms to define more precise subgroups within the ASD data subset. Both hierarchical and k-means clustering methods were applied, leveraging the combination of the positional grid matrix and the dataset's variable distance matrix to form interconnected clusters³⁸⁰. To determine an appropriate number of clusters, the within-cluster distances were calculated for various cluster counts. Visualization tools provided in R were used to analyze the total within-cluster sum of squares (WSS), assisting in the selection of an optimal cluster number³⁸².

In the study, radar plots were generated to visualize and compare the prevalences of various medical conditions across different clusters, both in their normal and normalized states³⁸³. Initially, radar plots depicted the actual prevalence data, offering a direct visualization of the conditions' distribution in their original scale across the clusters. This initial representation provided a baseline understanding of the absolute prevalence figures. Subsequently, the prevalence data for each condition across the four clusters was normalized using min-max normalization. This critical step scaled all values to a uniform range between 0 and 1, where 0 denotes the minimum and 1 the maximum prevalence of any condition across the clusters, making it indispensable for adjusting the wide variations in absolute numbers across conditions and ensuring that each condition's prevalence is comparable on the same scale.

With the data normalized, another set of radar plots were created, where each axis represented one of the clusters, and the points along an axis indicated the normalized prevalence of a medical condition in that cluster. This method of visualization facilitates direct comparison of multiple conditions across the clusters, highlighting the relative prevalence of each. It shows the distribution pattern of each condition's prevalence across the clusters as well as provide an intuitive understanding of complex patterns and differences which might not be as evident in tabular data. Radar plots, in both their normal and normalized forms, offer several advantages in comparative analysis. They allow for the visualization of uniformity and variability in the distribution of conditions' prevalences across clusters. Conditions with

similar prevalences across clusters appear as more circular shapes in the plots, indicating uniform distribution, while varied prevalences result in more elongated or irregular shapes, pointing to disparities among clusters. Furthermore, the area covered by the plot corresponding to each condition enables viewers to assess which conditions have relatively higher prevalence across the clusters. This dual approach of visualizing conditions in both their original and normalized states is particularly beneficial understanding the relative distribution of conditions across the ASD clusters. Through this method, the study enhances the clarity of the presented data and supports more informed decision-making and analysis, allowing for a comparison between the absolute and relative prevalences of conditions within each ASD cluster.

6.3 Results

Descriptive Statistics

This study leveraged the OMOP person, visit, and condition tables within the HIE dataset to extract cases of ASD and to delineate their comorbidity profiles along with demographic characteristics. The inclusion criterion for individuals into the study was the presence of one or more documented conditions, ensuring a comprehensive capture of relevant health data. A targeted extraction was conducted based on the ASD phenotype definition outlined in **Table 6.1**. **Table 6.3** provides total counts for the entire pediatric cohort and the ASD subset, detailing the demographics of the study's population. This includes a breakdown of specific demographic attributes such as age range and gender distribution within both the general and ASD-identified groups. There were a total of **19,754** individuals in the dataset for the time range January 2018 – April 2023, of which **455** were identified with a diagnosis of ASD, representing approximately 2.3% of the dataset. Thus, within this dataset, approximately 1 in 43 individuals was diagnosed with ASD. The demographics in the study reveal a notable discrepancy in gender distribution among the ASD population compared to the pediatric population. Males represent a larger proportion within the ASD group at 75.4%, which is significantly higher than the 50.4% prevalence in the general pediatric cohort. Conversely, females are less prevalent within the ASD population at 24.6%, compared to 49.6% in the total pediatric sample.

The study's observation of a larger proportion of males within the ASD group aligns with national trends. Age distribution is fairly consistent between the ASD and general populations, with the 4-8 and 14-18 age ranges being the most represented. Ethnicity shows a slight overrepresentation of non-Hispanic Latino individuals in the ASD group at 66.2%, compared to 61.7% in the broader group.

The analysis from **Table 6.4** reveals a significantly higher prevalence of various conditions in the ASD group, with notable increases in gastrointestinal (GI) conditions, asthma, and epilepsy alongside mental health conditions like suicidality. The study's findings indicate a significantly higher prevalence of various comorbidities in children with ASD compared to the entire pediatric population. Mental health conditions, notably, show a striking disparity. Suicidal thoughts and behaviors (STB) are reported in 10.3% of the ASD group versus 3.2% in the general pediatric population, with a p-value indicating a highly significant difference. Anxiety and depression are also considerably more prevalent in the ASD group, with 42.4% experiencing anxiety and 13.8% depression, again highlighting significant statistical differences. Beyond mental health, the study reveals higher rates of gastrointestinal conditions, epilepsy, and asthma in children with ASD. For instance, gastrointestinal symptoms are reported in 24.4% of the ASD group compared to 17.8% generally, and epilepsy shows a prevalence of 10.8% in ASD versus 2.6% in the broader pediatric cohort. These findings illuminate the complex care needs of children with ASD, emphasizing the importance of mental health support alongside management of other comorbid conditions. **Appendix B** provides more information on some of the common conditions and diagnosis groupings analyzed and characterized in this study. Codes of either CCS, PheCodes, or a combination of both is provided with notes providing definitions for broader groupings.

Table 6.5 delves into healthcare utilization differences between ASD and non-ASD pediatric patients through different proxies. It indicates significant differences in the use of healthcare services between ASD compared to the general pediatric population. Patients with ASD had higher median and mean numbers across all categories: visits, unique medications, and prescription fills, suggesting increased healthcare utilization. For example, the mean number of visits for ASD patients was 52 compared to 24 for the all-

pediatric group. Additionally, the prevalence of various diagnoses used as proxies for healthcare utilization showed statistically significant higher rates in the ASD group for conditions such as symptoms of illness, viral infections, socioeconomic and psychosocial factors, among others. Chi-square p-values indicated these differences were statistically significant, underscoring the increased healthcare needs of ASD patients.

Figure 6.4 in the results section presents a detailed comparison of healthcare utilization metrics between ASD and non-ASD populations within the HIE dataset, using box plots for visual representation. This comparison spans across four key metrics: (1) the total number of visits per patient throughout the lifetime of the HIE dataset, (2) the number of emergency department visits per patient, (3) the number of unique medications per patient, and (4) the number of lab orders per patient. Each sub-figure, labeled from **Figure 6.4.1 to 6.4.4**, elucidates utilization trends, indicating differences in healthcare engagement and requirements between the ASD and Non-ASD cohorts. These visual insights highlight the elevated healthcare needs and utilization patterns among patients with ASD compared to their non-ASD counterparts, reflecting on the complex care requirements associated with ASD.

Table 6.3: Demographics of the dataset comparing the entire pediatric population with the subset ASD population describing gender, age range, and ethnicity

	Pediatric Population		ASD Population		
TOTAL	19754		455		
	Count	Prevalence	Count	Prevalence	Non-ASD vs ASD X ² (p-value)
Sex					
Male	9959	50.4%	343	75.4%	1.95E-29* ↑
Female	9795	49.6%	112	24.6%	7.24E-25 ↓
Age Range					
0-3	613	3.1%	11	2.4%	0.44
4-8	5182	26.2%	126	27.7%	0.31
9-13	6856	34.7%	156	34.3%	0.87
14-18	7103	36.0%	162	35.6%	0.84
Ethnicity					
Hispanic Latino	5905	29.9%	137	30.1%	0.67
Not Hispanic Latino	12188	61.7%	301	66.2%	9.96E-03* ↑
Unknown	1661	8.4%	17	3.7	4.29E-04 ↓
All prevalence % calculated based on subgroup total (total counts in row 1)					
* = statistical significance as a difference in ASD group ($p < 0.05$)					
↑ = increase in ASD group; ↓ = decrease in ASD group					

Table 6.4: Prevalence of conditions in all pediatric patients vs. ASD subset with chi-square comparisons

	All Pediatric		ASD		
Total	19754		455 (2.3%)		
Diagnoses	Count		Count		Non-ASD vs ASD X ² (p-value)
Attention-Deficit/Hyperactivity Disorder (ADHD)	1401	7.1%	175	38.5%	5.49E-158 ↑
Adjustment Reaction	1018	5.2%	88	19.3%	3.32E-45 ↑
Allergic reactions	2442	12.4%	93	20.4%	3.18E-08 ↑
Anxiety	2355	11.9%	193	42.4%	4.61E-95 ↑
Asthma	1631	8.3%	60	13.2%	5.07E-05 ↑
Chromosomal Abnormalities	190	1.0%	92	20.2%	0 ↑
Conduct Disorders	679	3.4%	89	19.6%	2.56E-83 ↑
Congenital Anomalies	606	3.1%	70	15.4%	2.48E-55 ↑
Constipation	1531	7.8%	84	18.5%	6.95E-19 ↑
Depression	918	4.6%	63	13.8%	5.45E-22 ↑
Developmental Delays	672	3.4%	178	39.1%	0 ↑
Diabetes	357	1.8%	11	2.4%	0.29
Disruptive mood dysregulation disorder	217	1.1%	43	9.5%	7.70E-69 ↑
Eating Disorder	243	1.2%	34	7.5%	3.36E-33 ↑
Epilepsy; Seizures	518	2.6%	49	10.8%	1.04E-28 ↑
Esophageal disorders	444	2.2%	29	6.4%	7.89E-10 ↑
Headache/Migraine	1082	5.5%	37	8.1%	7.76E-03 ↑
Hearing loss	369	1.9%	38	8.4%	7.31E-26 ↑
Intellectual or Developmental Disability (IDD)	97	0.5%	25	5.5%	3.14E-55 ↑
Learning Disorders	298	1.5%	31	6.8%	1.23E-21 ↑
Muscle disorders	311	1.6%	36	7.9%	5.70E-29 ↑
Musculoskeletal Congenital Conditions	1019	5.2%	43	9.5%	1.38E-05 ↑
Nervous System Disorders	133	0.7%	17	3.7%	2.15E-16 ↑
Neuromuscular Disorders	150	0.8%	12	2.6%	1.90E-06 ↑
Nutritional Deficiency	923	4.7%	52	11.4%	1.34E-12 ↑
Obesity	1078	5.5%	48	10.5%	5.53E-07 ↑
Obsessive-compulsive disorder (OCD)	116	0.6%	17	3.7%	1.70E-19 ↑
PTSD/Acute Stress Reaction	769	3.9%	70	15.4%	5.74E-39 ↑
Schizophrenia/Psychotic Disorders	40	0.2%	12	2.6%	2.38E-32 ↑
Sleep Disorder	780	3.9%	96	21.1%	4.59E-83 ↑
Speech/Language Disorders	793	4.0%	153	33.6%	7.05E-239 ↑
Strabismus	142	0.7%	17	3.7%	4.67E-15 ↑
Substance Use Disorder	237	1.2%	13	2.9%	7.36E-04 ↑
Suicidal Thoughts and Behaviors (STB)	630	3.2%	47	10.3%	3.44E-19 ↑
Symptoms: Abdominal pain; Digestive	3514	17.8%	111	24.4%	6.64E-05 ↑
Symptoms: Malaise and fatigue	931	4.7%	49	10.8%	2.27E-10 ↑
Symptoms: Mental/Substance Use Conditions	991	5.0%	129	28.4%	2.29E-121 ↑
Symptoms: Nervous system	828	4.2%	107	23.5%	3.70E-99 ↑
Teeth and Gingiva Disorders	896	4.5%	73	16.0%	4.54E-34 ↑
Tics/Stuttering	185	0.9%	37	8.1%	4.52E-60 ↑
Urinary incontinence	359	1.8%	34	7.5%	1.36E-20 ↑
Vitamin Deficiency	860	4.4%	46	10.1%	3.91E-10 ↑

Table 6.5: Healthcare utilization: Average total number of visits per patient, emergency visits, unique medications, labs, and other diagnoses comparing ASD subset to the all-patient set.

Utilization	Non-ASD		ASD		
Number of Visits					
Mean (SD)	22.0 (27.8)		52.0 (51.7)		
Median	15.0		36.0		
Number of Emergency Visits					
Mean (SD)	4.3 (4.2)		7.0 (9.4)		
Median	3.0		4.0		
Number of Medications					
Mean (SD)	10.9 (9.9)		19.2 (13.9)		
Median	8.0		16.0		
Number of Labs					
Mean (SD)	49.5 (36.6)		65.3 (43.2)		
Median	43.0		58.0		
Diagnoses (CCSR groupings)	Count	Prev	Count	Prev	Non-ASD vs ASD X² (p-value)
Abnormal findings without diagnosis	1251	6.3%	62	13.6%	2.78E-11 ↑
Fluid and electrolyte disorders	319	1.6%	22	4.8%	1.73E-08 ↑
Lifestyle/life management factors	192	1.0%	14	3.1%	2.24E-06 ↑
Otitis media	1287	6.5%	49	10.8%	1.01E-04 ↑
Socioeconomic/psychosocial factors	219	1.1%	14	3.1%	3.27E-05 ↑
Symptoms: Circulatory	770	3.9%	29	6.4%	3.87E-03 ↑
Symptoms: Fever	2715	13.7%	75	16.5%	5.37E-02 ↑
Symptoms: Nausea and vomiting	1739	8.8%	64	14.1%	2.66E-05 ↑
Symptoms: Respiratory	3280	16.6%	81	17.8%	0.36
Symptoms: Skin/Subcutaneous	1155	5.8%	47	10.3%	1.80E-05 ↑
Viral infection	3328	16.8%	104	22.9%	2.02E-04 ↑

All prevalence % calculated based on subgroup total (total counts in row 1)
* = statistical significance as a difference in ASD group (*p* < 0.05)
↑ = increase in ASD group; ↓ = decrease in ASD group

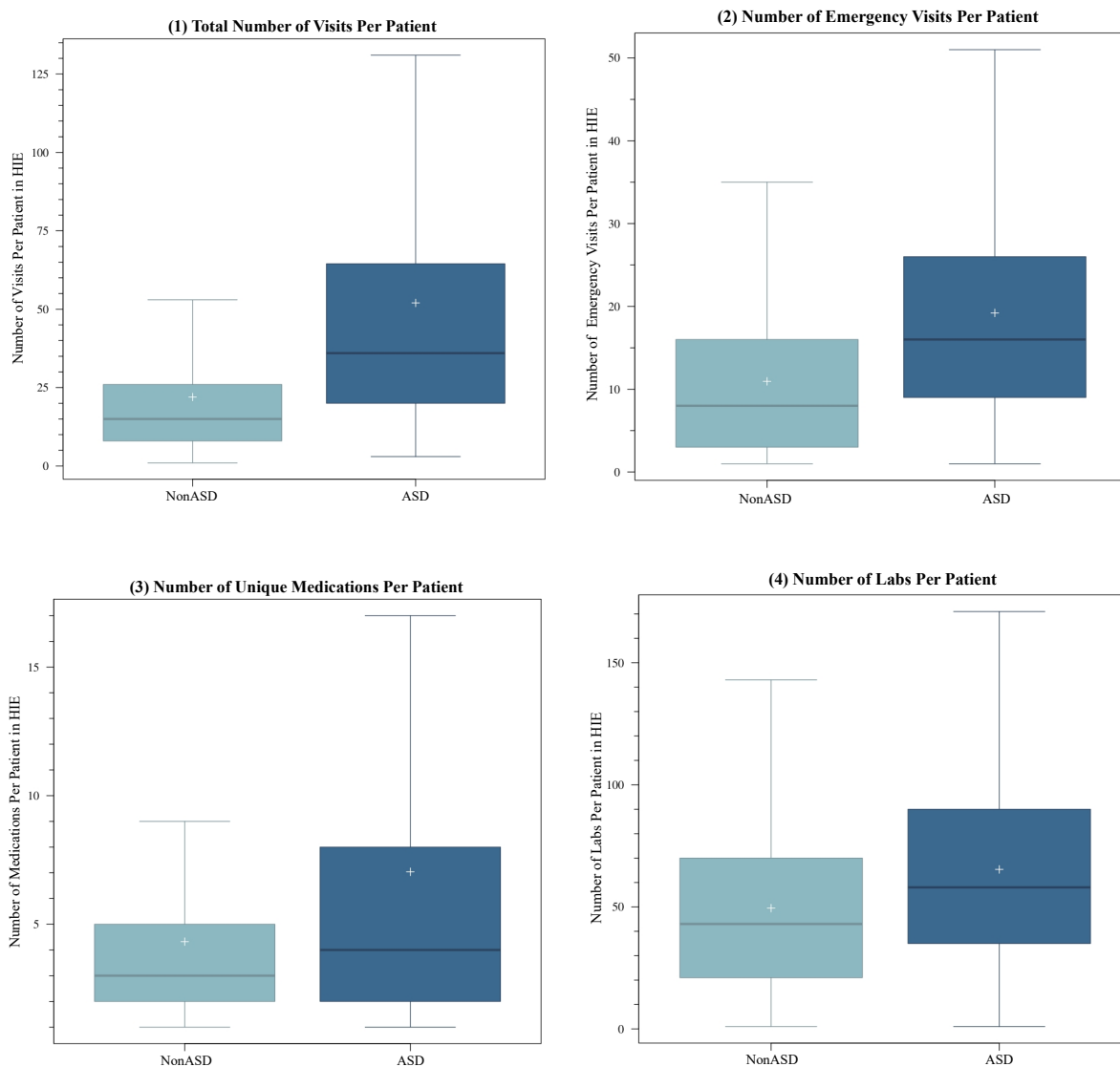


Figure 6.4: Healthcare Utilization – Box plots comparing different utilization measures between the Non-ASD and ASD subsets in the HIE dataset: (1) Total number of visits per patient (2) Number of emergency visits per patient (3) Number of unique medications per patient (4) Number of labs per patient (“+” = mean; Outliers removed)

Self-Organizing Map Clustering

This study looked at two separate SOM outputs to analyze the pediatric population, with a specific emphasis on ASD patients. For both analyses, the feature set did not include the ASD designation. The first algorithm was applied to the entire pediatric dataset to explore whether ASD patients form clusters based on their condition features. As seen in **Figure 6.5.1** the SOM revealed a balanced distribution of patients across the SOM, reflecting a diverse yet evenly represented pediatric cohort. **Figure 6.5.2** highlights the tendency for ASD patients to cluster together, indicating shared characteristics in their condition features. This outcome showcases the utility of SOM algorithms in discerning patterns within a heterogeneous patient population and is particularly insightful in identifying and understanding the unique features of ASD patients. Such findings are crucial for enhancing our understanding of ASD within the broader pediatric context.

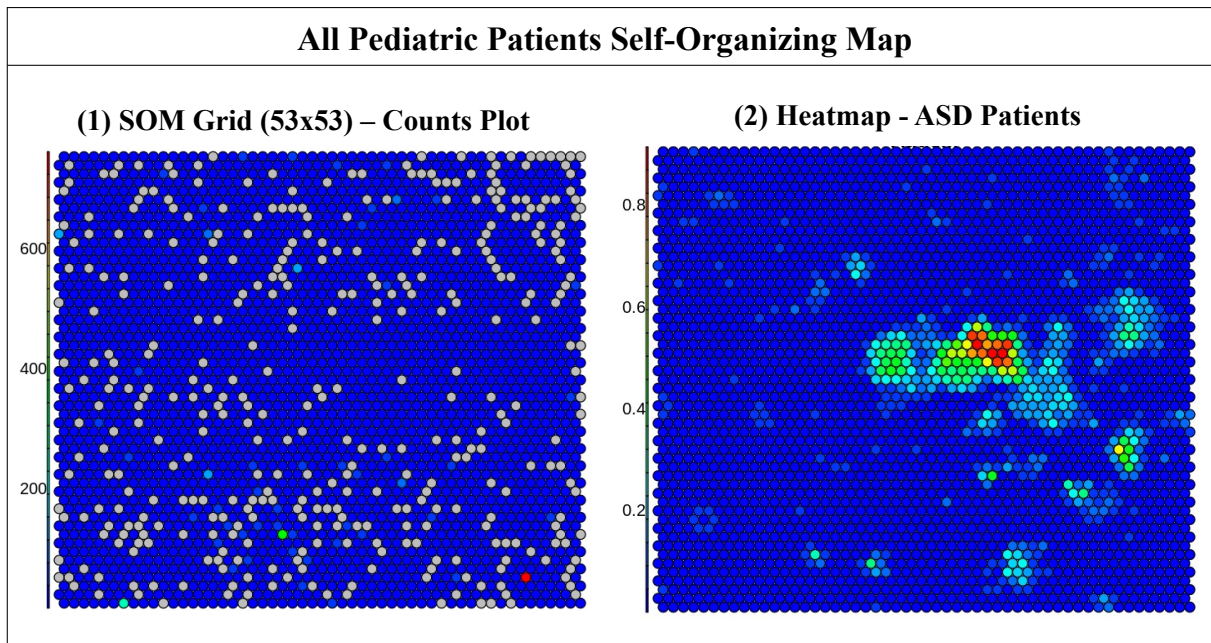


Figure 6.5: SOM of all pediatric patients in the dataset

The cluster analysis was executed utilizing a SOM configured with a 20x20 grid and an adaptable learning rate. The final SOM map can be seen below in **Figure 6.6**. **Figure 6.6.1** shows a count mapping plot for

the SOM to visualize the distribution of data across the SOM grid. This plot effectively demonstrates the frequency of data points in each node of the map, highlighting areas of high density that correspond to clusters within the dataset. Through this visualization, patterns and relationships among the data points were discerned, providing valuable insights into the underlying structure of the dataset, and facilitating the identification of similar groups based on the mapped characteristics. **Figure 6.6.2** illustrates a codes plot for the SOM, showcasing the distribution and organization of the dataset's variables across the SOM grid. This plot visualizes the weight vectors as codes in each node, representing the characteristic features of the data points clustered around that node. The variation in the codes across different nodes reflects the diversity of the dataset, enabling the identification of patterns, similarities, and differences among the data points. This visualization aids in understanding the high-dimensional data structure through the SOM's two-dimensional representation. **Figure 6.6.3** shows a neighbors distance plot for the SOM visually represents the distances between neighboring nodes within the SOM grid. This plot is instrumental in illustrating the topology of the data, with the distances between nodes indicating the degree of dissimilarity. Such a plot is crucial for understanding the data's structure, identifying distinct clusters, and highlighting areas of the map where data points are closely related or significantly different, thereby providing a deeper insight into the underlying patterns within the dataset.

To ascertain the optimal quantity of clusters, various metrics were used. **Figure 6.7** elucidates the mean within-cluster distance; the discernible inflection point suggests a significant value for k . Employing both K-means and hierarchical clustering methods to segment the map units into classes, K-means was found to yield better-connected clusters. Consequently, it was selected for the SOM clustering. Based on the elbow plot and visual examination of connected clusters and feature similarities, four clusters were determined to be optimal.

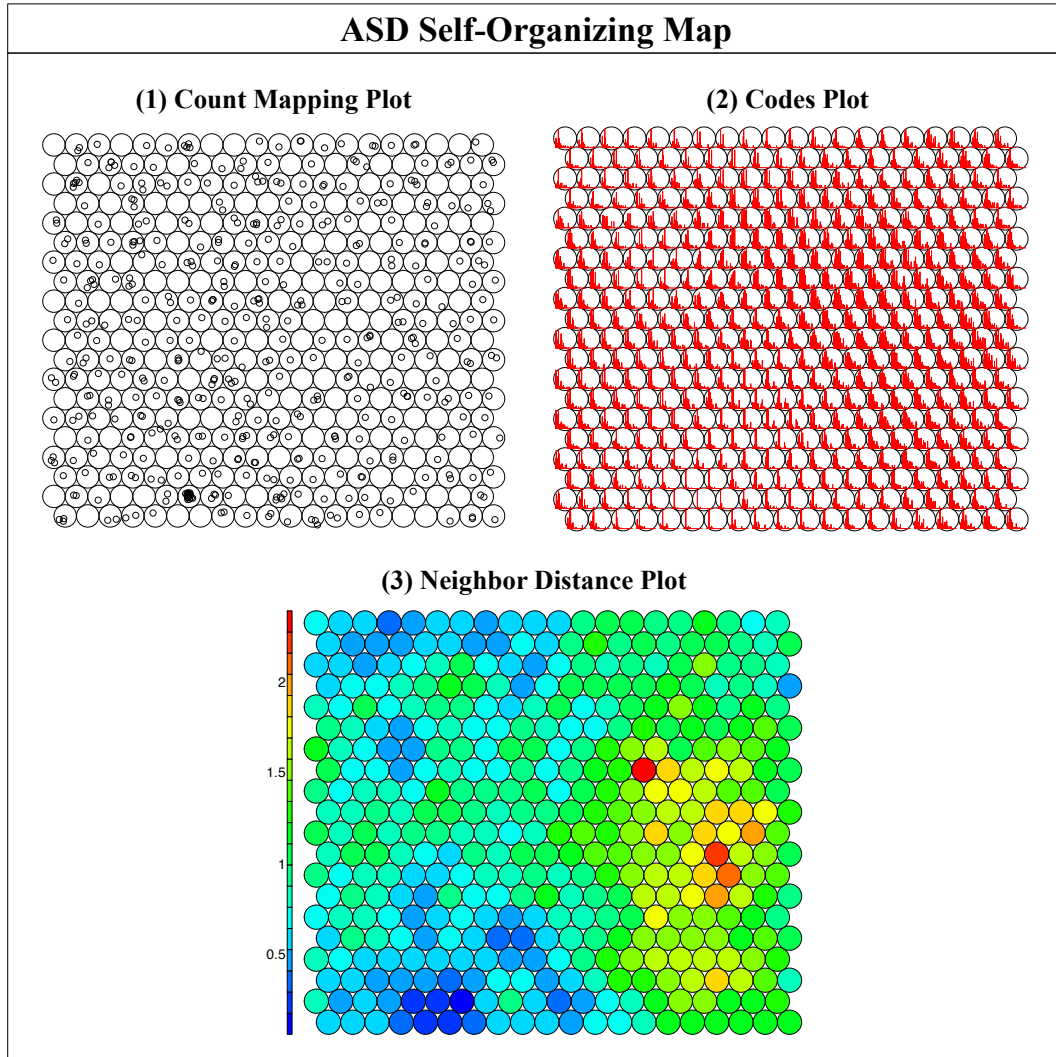


Figure 6.6: Visualizing data structure and similarities in ASD SOM

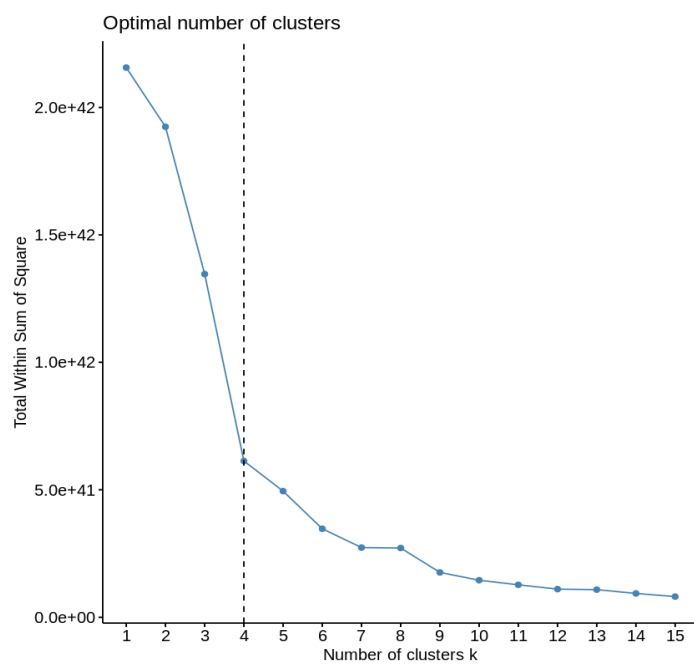


Figure 6.7: Elbow plot depicting the variation in total within-cluster sum of squares (WSS) across different cluster counts.

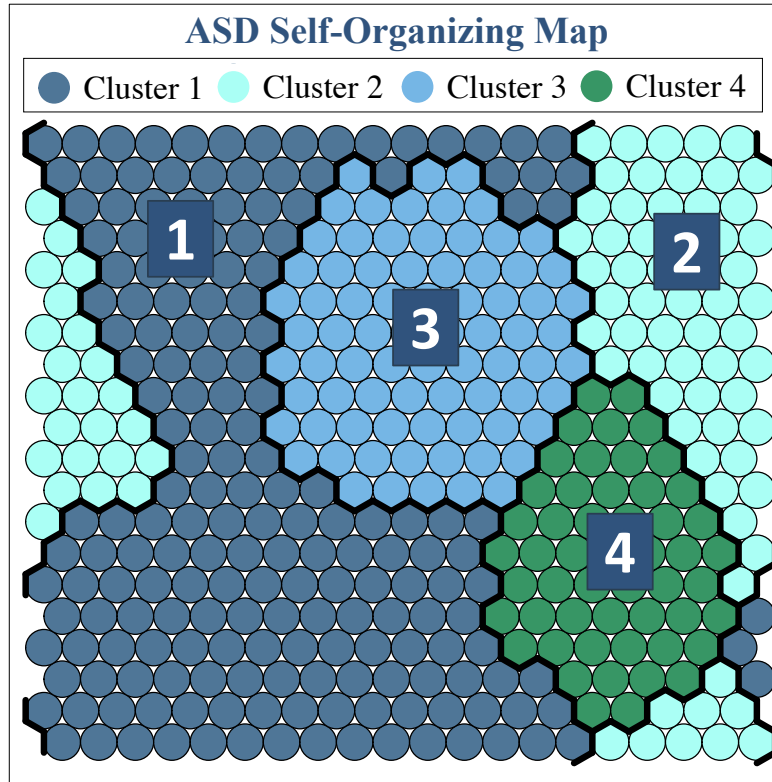


Figure 6.8: Final SOM grid with boundaries and labeled clusters.

Figure 6.8 delineates the final SOM output, presenting the definitive boundaries of the four clusters for ASD patients. The results showcased in **Figure 6.9** specifically highlight the localization of common mental health conditions such as depression, anxiety, sleep disorders, and STB on the SOM. This visualization highlights the clustering of these mental health issues within certain regions of the map, offering insights into their prevalence and co-occurrence patterns. Conversely, **Figure 6.10** extends the analysis to other diagnostic categories and condition groupings, including asthma, abdominal pain, and headache, illustrating their distribution across different areas of the SOM, and providing a broader perspective on the range of health conditions examined.

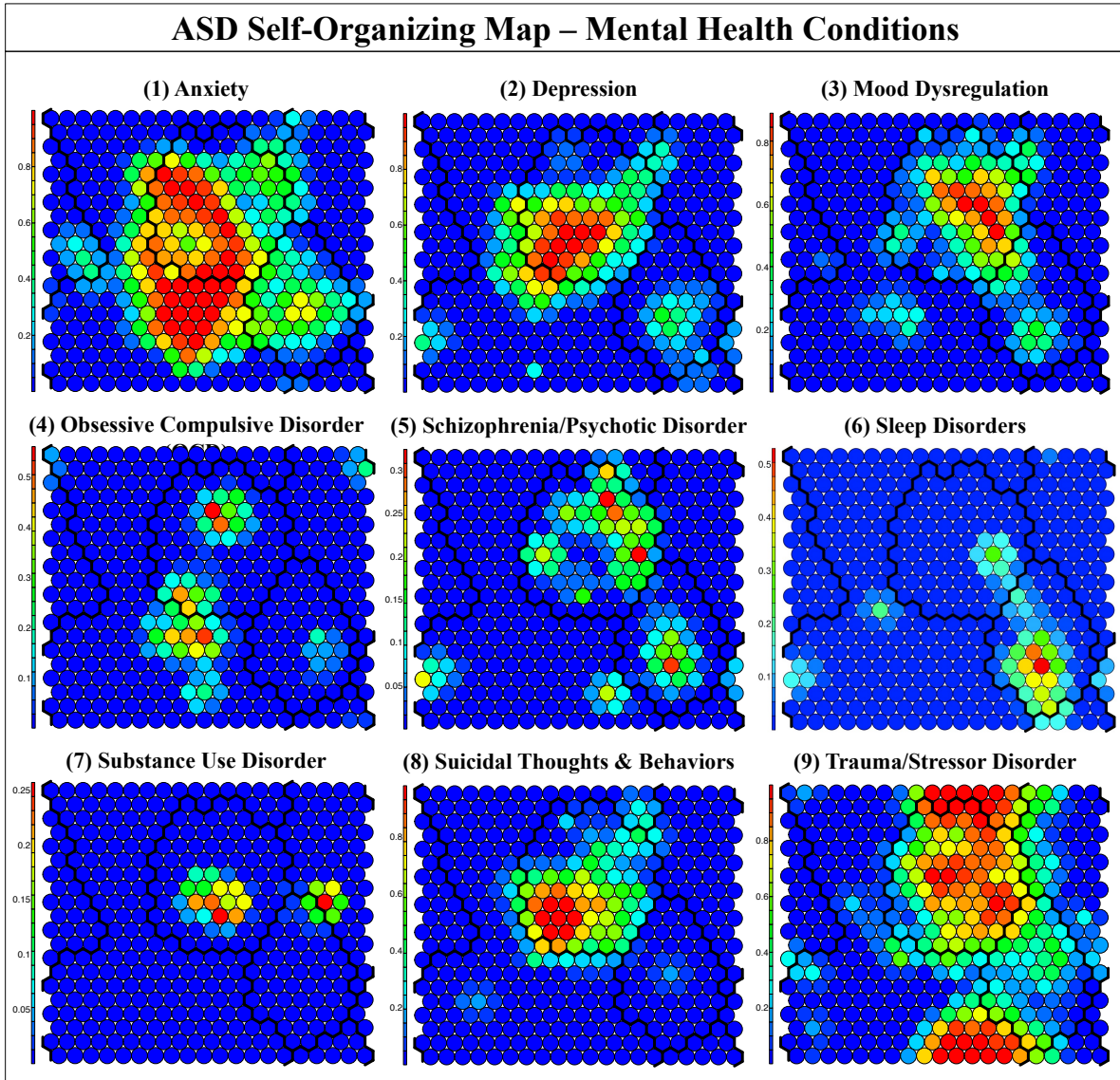


Figure 6.9: Heat maps for mental health CCSR categories highlighting regions of increased density within the final SOM output.

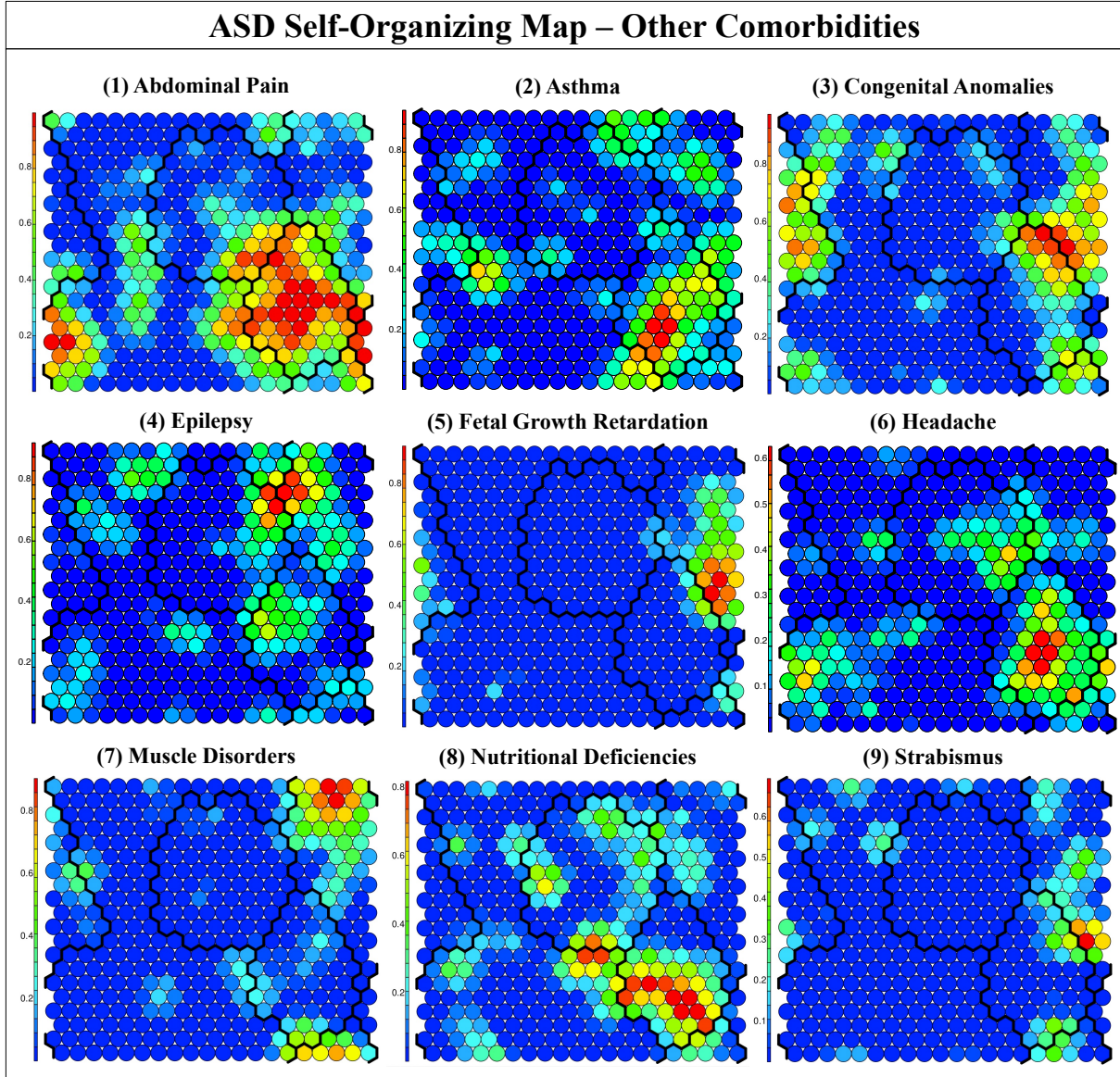


Figure 6.10: Heat maps for various CCSR categories highlighting regions of increased density within the final SOM output.

Table 6.6: Cluster sizes and demographics

	Cluster 1		Cluster 2		Cluster 3		Cluster 4	
Total	247		87		78		43	
Sex								
Male	186	75.3%	66	75.9%	59	75.6%	32	74.4%
Female	61	24.7%	21	24.1%	19	24.4%	11	25.6%
Hispanic/Latinx	62	25.1%	45	51.7%	18	23.1%	11	25.6%
Average Age Range	9-13		5-9		12-16		8-12	

In the analysis of the 455 individuals diagnosed with ASD we delineated four distinct clusters, each showcasing unique patterns of demographic and clinical characteristics. The demographic features such as sex, average age range, and ethnicity for each cluster are detailed in **Table 6.6**. An examination of each cluster was undertaken by evaluating the prevalence of CCSR categories, alongside a comparison of some of the most frequently observed conditions.

Visualization of the cluster analysis is presented in **Figure 6.11**, which combines radar plots of all clusters, providing a juxtaposed view of condition prevalences in **Figure 6.11.1**, and a normalized comparison in **Figure 6.11.2** for enhanced clarity. Furthermore, **Figure 6.12** delves into each cluster individually, offering a detailed exploration of specific features of interest and their representation within each cluster. The size of the polygon vector in these radar plots serves as a direct indicator of condition prevalence within a cluster—a larger polygon signifies a higher prevalence rate. Notably, Cluster 3 is characterized by a significant prevalence of mental health conditions, including depression, PTSD, and STB. Below is a concise descriptive summary for each cluster, providing insights into their characteristics and prevalent conditions:

Cluster 1: Comprising 247 individuals, this cluster shows a predominantly male population (75.3%). The average age is approximately 9-13 years. Notable conditions in this cluster include Asthma and Epilepsy/Seizures.

Cluster 2: Encompassing 87 individuals, the gender distribution is slightly more balanced with 75.86% male. The average age is youngest across the clusters, at around 5-9 years. Significant conditions prevalent in this cluster are Developmental Delays, Cerebral Palsy, Speech/Language Disorders and Muscle Disorders.

Cluster 3: This cluster has 78 individuals. It is characterized by the highest average age range at 12-16 years old. Noteworthy conditions include a high prevalence of mental health conditions such as Depression, Anxiety, PTSD, ADHD, Conduct Disorders, Adjustment Reaction, Personality Disorders, Bipolar, and STB.

Cluster 4: The smallest cluster, with 43 individuals, has a slightly higher female presence (25.58%). The average age range is 8-12 years. It is distinguished by conditions such as Abdominal Pain, GERD, Constipation, Nutritional Deficiencies, Vitamin Deficiency, Headaches, Sleep Disorders, and Asthma.

Figure 5.13 presents a stacked bar chart that elucidates the distribution of various conditions within the ASD population across clusters. Unlike radar plots, which provide a detailed view of condition prevalence within individual clusters, the stacked bar chart in this figure aggregates the data to show the total counts of each condition across the entire ASD cohort. This method of visualization enables a comparative analysis of condition frequencies within each cluster and across the population. It offers an at-a-glance understanding of how individuals with different conditions are distributed among the clusters, thereby highlighting patterns that may be critical for targeted interventions or further research into the heterogeneity of ASD. The results from this analysis demonstrates the utility of SOM clustering in discerning subgroups within pediatric patient populations, even when diagnostic labels are omitted from the clustering inputs.



Figure 6.11: Cluster visualization with Radar Plots - (1) illustrating condition prevalence across clusters and (2) normalized comparisons.

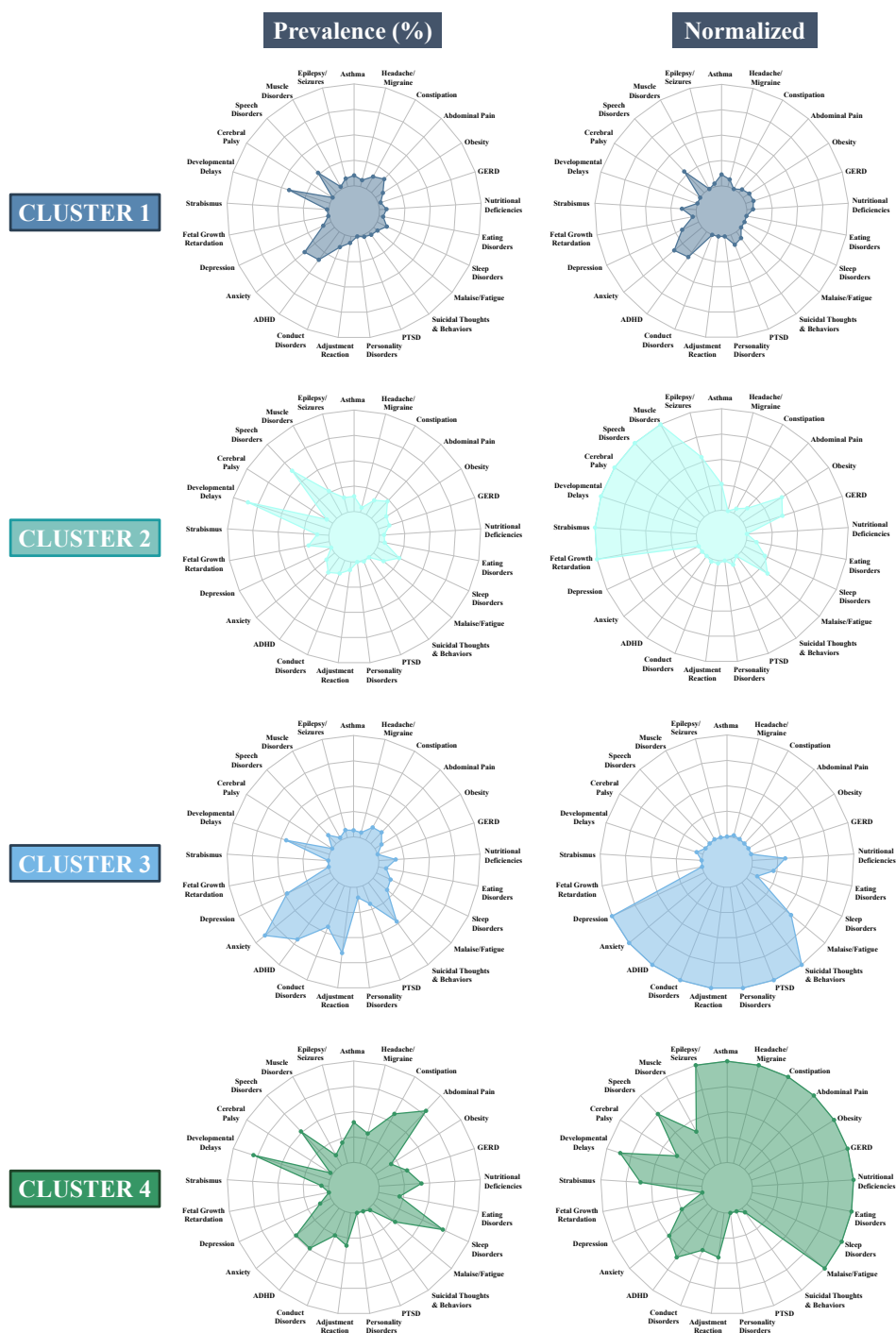


Figure 6.12: Individual radar plots for each cluster depicting condition prevalences and normalized plots.

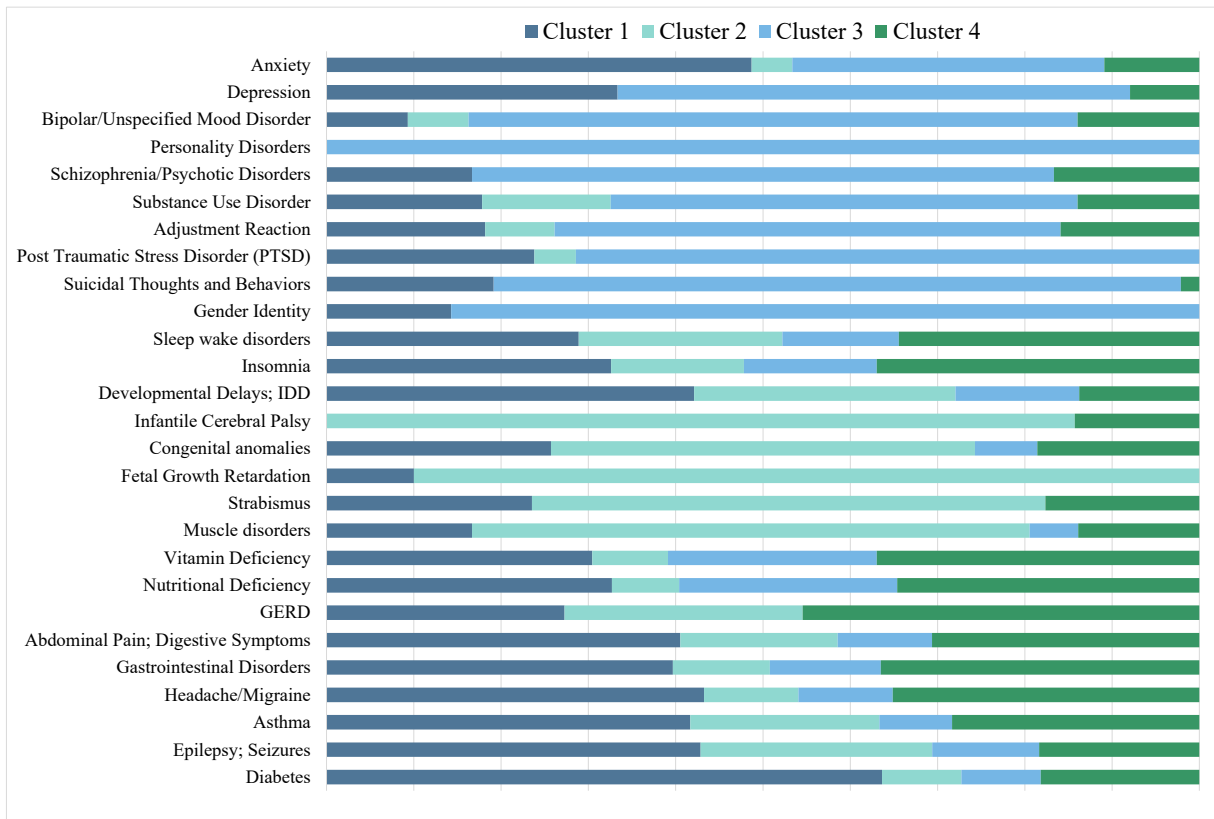


Figure 6.13: Stacked bar chart displaying the number of ASD patients per condition and their distribution across different clusters, clarifying condition-specific prevalence within the cohort.

6.4 Discussion

This study examined the prevalence of co-occurring conditions and mental health diagnoses among individuals with ASD using pediatric clinical data from a statewide HIE. By employing unsupervised machine learning techniques, this study aimed to identify patterns and clusters within the ASD population, offering a better understanding of the phenotypic profiles and comorbidity burdens that may elevate mental health risks in this group. The primary objective of this study was to validate the hypothesis of increased comorbid conditions and mental health diagnoses in individuals with ASD. Additionally, this study aimed to characterize the pediatric dataset from the HIE and describe the patient profiles within the identified clusters of the ASD subgroup.

The characterization of the population revealed that most conditions were significantly more prevalent in the ASD population compared to non-ASD counterparts, as evidenced by chi-square test results. The clusters identified through unsupervised machine learning techniques exhibited specific properties, indicative of the heterogeneity within the ASD population. Cluster 1 emerged as the largest, encompassing a broad spectrum of conditions. Notably, it did not exhibit any single condition that was highly distinctive, although there was a higher incidence of asthma, epilepsy, and anxiety observed. Cluster 2, with the largest prevalence of Hispanic/Latinx (51.7%), had the youngest individuals on average, ranging from 5 to 9 years. This cluster presented with numerous conditions suggestive of higher support needs, such as developmental delays, speech disorders, cerebral palsy, and muscle disorders. Cluster 3 had the oldest individuals, aged between 12 to 16 years, and was characterized by a significant proportion of mental health conditions, including depression. It was especially marked by severe mental health issues like STB, PTSD, bipolar disorder, personality disorder, and conduct disorder. Lastly, Cluster 4 was distinguished by a prevalence of chronic conditions and gastrointestinal issues, such as asthma, headaches, abdominal pain, sleep disorders, and nutritional deficiencies.

Incident rates of mental health disorders, including anxiety, depression, and ADHD, were higher in the ASD subgroup compared to non-ASD counterparts. Clustering techniques delineated distinct groups within

the ASD population, each with unique comorbidity profiles. The heightened rates of mental health disorders within the ASD subgroup suggest a critical need for early intervention and specialized mental health services. These findings also highlight the importance of routine screening for mental health conditions in this population. The clusters identified offer valuable insights into the heterogeneity of ASD and its associated conditions. The prevalence of specific comorbidities within these clusters demonstrates the need for tailored approaches to treatment and care. Building on this foundation, the study also significantly contributes to the advancement of early identification strategies for ASD cases. By elucidating the profiles and characteristics inherent in the ASD population, this research lays the groundwork for developing predictive models that can aid in the diagnosis of ASD at earlier stages.

The use of data mining and unsupervised machine learning techniques, such as SOMs, enables the identification of specific patterns and risk factors associated with ASD. This approach enhances understanding of the disorder and paves the way for the creation of tools that can predict ASD with greater accuracy and speed. Moreover, the study takes an important step forward by proposing the next stages of research, which include the development of predictive modeling frameworks. These models aim to assist in the early diagnosis of ASD as well as categorize risk levels for associated conditions, such as adverse mental health outcomes. By identifying individuals at higher risk for such comorbidities, it becomes possible to implement preventive measures and interventions at an earlier stage, thereby improving the overall prognosis for those with ASD.

In summary, this research extends beyond the identification of co-occurring conditions in individuals with ASD towards the development of early detection and predictive modeling techniques. These advancements hold the promise of revolutionizing the approach to diagnosing ASD, allowing for earlier and more personalized interventions. The emphasis on predictive modeling and risk categorization for adverse mental health outcomes further emphasizes the potential of this research to improve the quality of life for individuals with ASD through targeted and effective care strategies.

Using HIE data in this study offers a major benefit by providing access to a wide range of real-world clinical information from many patients. This approach helps to get a more complete picture of ASD-related conditions, offering a view that is often not possible with smaller, isolated datasets. The use of HIE data provides a population-level perspective, though it is not without limitations. The accuracy of the findings is contingent on the quality of data recorded in the HIE. Furthermore, the study's observational nature precludes causal inferences. Further research is necessary to validate these findings in different populations and to explore the effectiveness of targeted interventions based on the identified patient profiles.

6.5 Conclusion

This study confirms that there are increased co-occurring conditions and mental health diagnoses in individuals with ASD. Through the characterization of the HIE pediatric dataset and the clustering of ASD individuals, this work provides understanding of the complex clinical features and groupings of this population. The insights gained can inform clinical practice, emphasizing the necessity for integrated care pathways that address the multifaceted needs of those with ASD. The findings advocate for a multidisciplinary approach, one that integrates the various specialties and services essential to manage the multiple aspects of ASD. This supports the overarching aim of delivering patient-centered care that is both effective and sensitive to the unique challenges faced by these individuals and their families.

6.6 Acknowledgements

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of RIDOH, RIQI, and the National Institutes of Health. The work was conducted using computational resources and services provided by the Center for Computation and Visualization at Brown University. De-identified data from CurrentCare were provided by RIQI for the study period January 2018 – April 2023. This dataset contained lab-confirmed, suspected, and possible cases of COVID-19. These cases were demographically matched (on age group, sex, race, and ethnicity) to controls who tested negative or equivocal for COVID-19, at a ratio of 1:2 (cases to controls).

Chapter 7: Aim 2(d)- Characterizing Autism Spectrum Disorder and Predicting Suicide Risk for Pediatric Psychiatric Emergency Services Encounters

List of Chapter Acronyms

ADHD = Attention-Deficit/Hyperactivity Disorder
ASD = Autism Spectrum Disorder
AUC = Area Under the ROC Curve
CV = Cross-Validation
C-SSRS = Columbia-Suicide Severity Rating Scale
ED = Emergency Department
EHR = Electronic Health Record
HPI = History of Present Illness
OCD = Obsessive-Compulsive Disorder
PES = Lifespan Pediatric Behavioral Health Emergency
Services/Pediatric Psychiatry Emergency Services
PTSD = Post-Traumatic Stress Disorder
ROC = Receiver Operating Characteristic
SHAP = Shapley Additive exPlanations
SVC = Support Vector Classifier
STB = Suicidal Thoughts and Behaviors
UML = Unified Modeling Language
XGBoost = Extreme Gradient Boosting

Preface

A version of this chapter has been previously presented at the 2023 American Medical Informatics Association (AMIA) Symposium and published in the associated conference proceedings³⁸⁴. An abstract for the workflow analysis was presented at The Patient and the Practitioner in the Age of Technology: Promoting Healing Relationships 2021.

This chapter begins with a workflow analysis conducted with the Lifespan Pediatric Behavioral Health Emergency Services (PES), aiming to comprehend the complex psychiatric services in Rhode Island and enhance understanding of data flow and collection practices. The workflow analysis delineates the pathways and data management practices within pediatric psychiatric services, crucial for understanding

data extraction methodologies and enhancing patient care pathways, ultimately driving improvements in clinical efficiency and outcomes.

Building upon the computational framework established in Aim 2, this workflow overview then transitions to characterizing individuals with autism spectrum disorder (ASD) using data from PES, aiming to better understand risk factors for suicidal thoughts and behaviors within this population. Individuals diagnosed with ASD are at a higher risk for mental health concerns including STB. Limited studies have focused on suicidal risk factors that are more prevalent or unique to the population with ASD. This study sought to characterize and classify youth presenting to the psychiatric emergency department (ED) for a chief complaint of STB. The results of this study validated that a high number of patients with ASD present to the ED with STB. There were important differences in clinical characteristics to those with ASD versus those without. Clinical features that showed important impact in predicting high suicide risk in the ASD cases include elements of the mental status exam such as affect, trauma symptoms, abuse history, and auditory hallucinations. Focused attention is needed on these unique differences in ASD cases so that suicide risk level can be appropriately and promptly addressed.

7.1 Workflow Analysis

Healthcare systems are complex networks that benefit greatly from the insights provided by clinical workflow analysis to enhance quality and efficiency¹⁶³. This analysis was performed to inform better understand how data is collected and in the psychiatric ED. In addition, the workflow analysis was performed to better understand the clinician workflow and how the different psychiatric services in the state connect. A deep understanding of existing workflows within the Electronic Health Record (EHR) system is essential for the effective use of its data³⁸⁵. Employing diagramming techniques to map out these workflows aids multidisciplinary teams in comprehending and improving current procedures in addition to highlighting opportunities for improving patient safety and care³⁸⁶. For instance, analyzing the timing within workflows can expose delays, allowing for strategic technological interventions that streamline care delivery and potentially enhance patient outcomes³⁸⁷. Moreover, this analysis can pinpoint where current

technologies, such as EHRs, may be hindering clinical efficiency, guiding enhancements that facilitate smoother interactions between patients and clinicians.

Lifespan, Rhode Island's premier health system encompassing pioneers like Hasbro Children's Hospital and Bradley Hospital, has been at the forefront of pediatric behavioral health through its Lifespan Pediatric Behavioral Health Emergency Services (PES). PES is a critical provider for children in acute behavioral health crises, offering evaluations and managing an increasing volume of crisis calls through the Kids' Link hotline. Despite the service's aim to reduce unnecessary ED visits, there has been a notable uptick in such visits, demanding an analysis of the underlying risk factors and causes. PES is the primary touchpoint for the youth in crisis across the state, capturing a wealth of clinical data within the Lifespan EHR. This repository contains demographic details, symptom descriptions, and socio-familial contexts, enriched with systems-level information such as geographic coverage and insurance types. However, the current format of this data repository poses challenges to straightforward data mining for pattern analysis and outcome tracking. One objective is to develop a comprehensive longitudinal database, extracting and storing the HER data from these services, capturing the clinical, operational, and research facets of interest.

The foundational step towards this goal is a methodical clinical workflow analysis across the variety of pediatric psychiatric services in the state. This was initiated through consultations with healthcare professionals, including physicians and social workers, to delineate existing patient care pathways and data management practices. Unified Modeling Language (UML) diagrams allow for visualization and analysis of the sequence and interconnectivity of current procedures and systems. Given the complexity of the healthcare environment and the multiple junctures for data entry, such analysis is indispensable. By mapping out these workflows, critical junctures for data extraction are identified, paving the way for the creation of a database to carry out research endeavors and address clinical quality and safety questions. Subsequent data analysis, leveraging machine learning and computational methodologies, will allow for a better understanding of the surge in ED psychiatric visits, among other research inquiries, ultimately driving improvements in patient care and outcomes within PES and beyond.

Navigating the complexities of clinician, patient, and data flow within the pediatric behavioral health services necessitated a foundational step – a formal workflow analysis. The initial objective of this analysis focused on understanding data flow and the details of the psychiatric services so that data could be properly extracted. However, workflow analysis extends beyond this singular purpose, offering multiple benefits.

The diagramming of workflows facilitated an in-depth comprehension of the complex structure and processes inherent to Rhode Island's pediatric mental health services. These visual representations, created through UML mapping, served as tool in the project to visualize the psychiatric services and complex nature of how each service interconnects and operates. The workflow diagrams provide a clear and structured visual framework of the current clinical pathways and data flow, thereby enabling the identification of the precise points for data retrieval. Furthermore, clinical workflow analysis and process mining have the added advantage of pinpointing opportunities for enhancing patient care and outcomes. By examining the sequences and intersections of various workflows, we can identify areas where efficiency can be improved, where bottlenecks occur, and where patient care pathways can be streamlined. This understanding paves the way for implementing changes that can lead to more effective, timely, and patient-centered care. In conclusion, the workflow diagrams produced from this analysis are instrumental for the technical goal of data extraction and serve as a springboard for broader quality improvements within PES. They allow for visualization and refinement of the complex processes that support the mental health services for children in Rhode Island, with the goal of improving both the quality and efficiency of care provided.

Figure 7.1 provides a visual representation of the workflow analysis for pediatric psychiatric services within Rhode Island's healthcare system. The figure is segmented into various components that map out the processes and data flow for pediatric behavioral health services.

Central to the diagram is the concept of 'Access,' signifying the focus on ensuring that the range of services provided is accessible to those in need. Another key service is Kids' Link RI, a 24/7 phone triage system for patients and families. The workflow for Kids' Link RI is detailed, capturing critical data such as the time of the call, the caller's details, and the nature of the complaint, which helps in determining the urgency

and type of follow-up required. The PES section is the main focus of the workflow diagram detailing the patient journey from arrival in the emergency department through triage, clinician evaluation, and eventually to discharge or transfer. The workflow emphasizes the development of safety plans which indicate some of the discharge workflows of these services. The interconnectedness of the emergency services with other healthcare provisions within the state is also depicted. Relationships with inpatient units at Hasbro Children's Hospital, Bradley Hospital, and various outpatient services are illustrated, showing the continuity of care pathways available to patients post-emergency care. The figure encapsulates the goal of the workflow analysis which is to identify and implement improvements in patient safety and care by streamlining service delivery and enhancing the effective use of EHR data. This analytical approach is crucial for integrating technological advancements into clinical practice and addressing the increasing volume of crisis calls and emergency department visits.

In the PES section of **Figure 7.1**, the diagram illustrates the flow of data that is integral to understanding and improving the pediatric psychiatric services. It demonstrates how data is captured at each step of the patient's journey, beginning with emergency triage, followed by clinician evaluation, psych consults, and boarding if necessary, leading up to the point of discharge or transfer. This pathway is crucial as it pinpoints where in the system each piece of data is collected, providing a roadmap for data extraction. Data management within the system is divided into track board data, managed via Excel and detailing room assignments and bed statuses, and EHR data. The data captured in this process is multifaceted, encompassing various structured and unstructured data elements. Structured data includes demographic information, clinical scores, and medical history, all of which are important to aid in research studies and quality and safety goals. Unstructured data, such as notes from initial evaluations, provide deeper insights into patient conditions and the context of each case.

Understanding the data flow within PES is essential for locating important data elements within the EHR for subsequent extraction and analysis. This workflow aided in understanding the data needed for the next section of the chapter, which uses the extracted data to analyze patterns, identify trends, and describe ASD

patients that present to the ED in crisis. Through the description and examination of this workflow and the associated data flow, stakeholders can discern inefficiencies and bottlenecks, thereby identifying opportunities for to enhance service delivery, improve patient outcomes, and streamline the overall process of care within the Rhode Island pediatric psychiatric services.

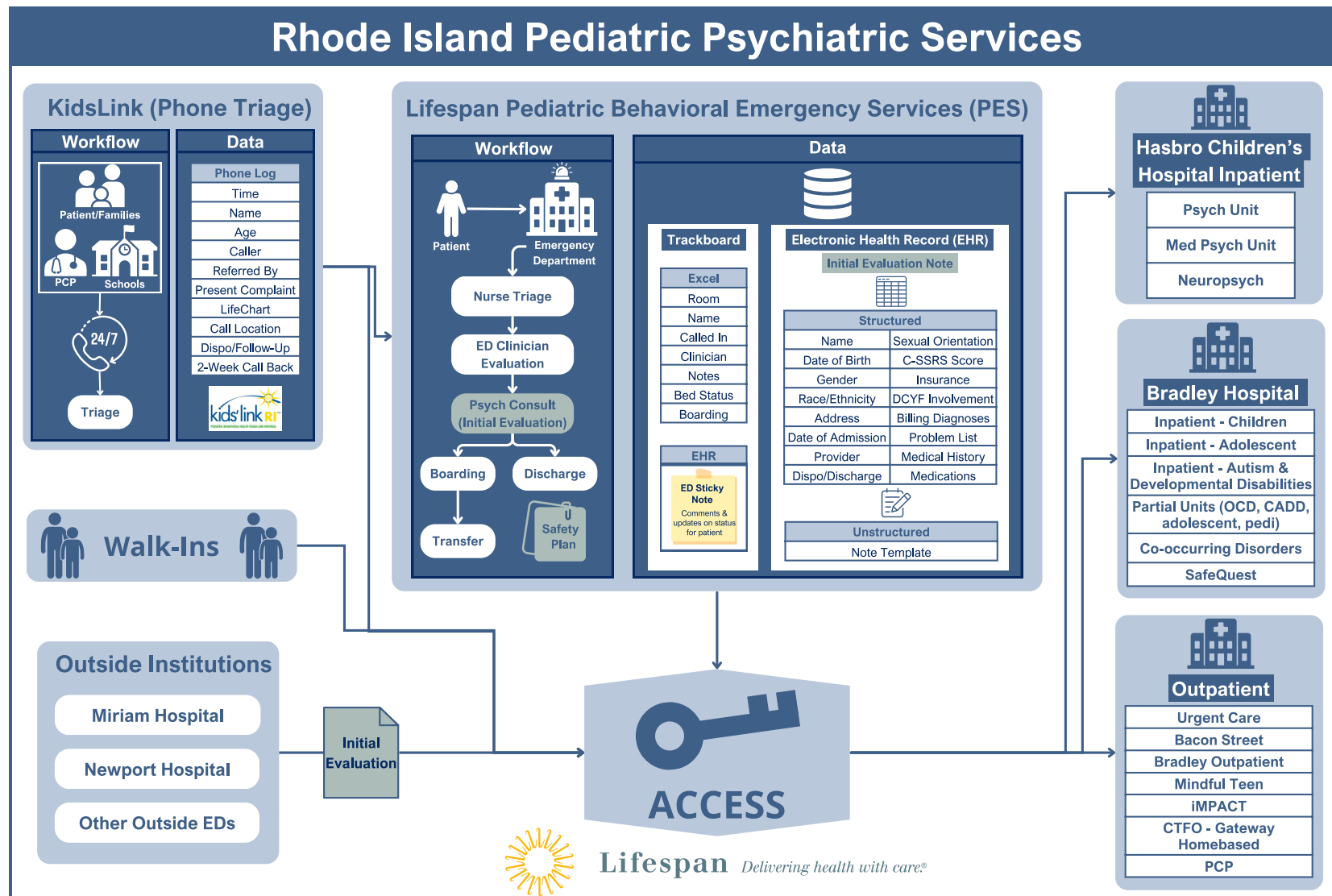


Figure 7.1: Clinical Workflow and Data Management Analysis of Rhode Island Pediatric Psychiatric Services

7.2 Introduction

Behavioral health acute crises continue to rise and burden pediatric psychiatric emergency departments nationwide.³⁸⁸ In December of 2021, the Office of the Surgeon General released an advisory with a need for focused attention and resources towards the youth mental health crisis in the United States.³⁸⁹ Further understanding of the different populations and characteristics of children presenting to the ED in crisis is needed. ASD is a neurodevelopmental disorder that has a wide range of presentations including behavioral impairments, poor social-emotional reciprocity, communication abnormalities, and repetitive behaviors.⁴ Diagnosis rates of ASD continue to rise and according to the latest report by the Centers for Disease Control and Prevention (CDC), 1 in 44 children were identified with ASD.³⁴⁷ ASD is associated with poor outcomes including social barriers, occupational challenges, educational delays, high stress, and poor transition into adulthood.^{390–392} Individuals with ASD have a high rate of co-occurring conditions compared to the rest of the pediatric population.^{7,9–12,14,15,366} Previous studies have identified that youth with ASD are at high risk for being diagnosed with one or more co-occurring psychiatric conditions.^{8,16,338,339} Additionally, a growing number of recent studies have found that individuals with ASD appear to have higher rates of STB which include suicidal ideation, suicide attempt, and death by suicide.^{27,31,393,394} Some literature has shown greater than three times higher suicide risk compared to those without ASD.^{32,395} There is thus a need to describe the unique clinical presentations and risk factors for STB in this population.

Further efforts are needed to better understand how youth with ASD in crisis present with STB and elucidate what areas of focus are needed to reduce risk and prompt early intervention. The Columbia-Suicide Severity Rating Scale (C-SSRS) is a common tool used to screen for STB and supports risk assessment.³⁹⁶ Although studies have indicated the usefulness of this tool,³⁹⁷ there have also been well documented general limitations in addition to challenges in administering the questionnaire on youth with ASD.^{398–400} A few studies have focused on suicidal risk factors that could be more prevalent or unique in the population with ASD, but more research is needed to validate and further explain how to identify and explain these and additional risk factors.^{401,402} Limited studies have used computational techniques to study individuals with

ASD presenting with STB using retrospective EHR data, and more specifically, data extracted from clinician notes. Information extraction methods can be used to extract important clinical information from narrative in the EHR and provide a more holistic understanding of a population of interest. Statistical and machine learning methods can aid in identifying important clinical features of focus and elicit patterns to gain knowledge and understanding. This study aimed to extract, analyze, and compare clinical features from encounters of individuals with ASD in behavioral crisis presenting to a pediatric psychiatric ED.

7.3 Methods

As **Figure 7.2** illustrates, this study sought to identify individuals with ASD and STB encounters in a pediatric psychiatric ED by using features derived from structured and unstructured EHR data. These encounters were characterized, and predictive models were developed to further explain and rank the impactful features for the population with ASD presenting with STB. All data preprocessing, statistical analysis, and machine learning were performed using Python (3.9.7).⁴⁰³

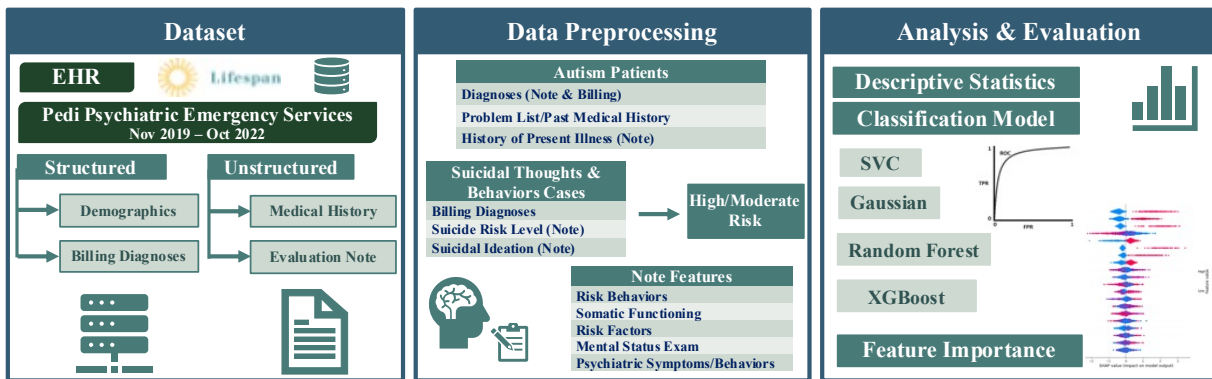


Figure 7.2: Overview of Study Approach

Dataset

The study data were extracted from an administrative and clinical dataset developed by pediatric psychiatry emergency services (PES) working in a pediatric ED within an academic health center in Rhode Island with Institutional Review Board approval. Patients evaluated by PES are referred by the pediatric ED medical team when presenting with high acuity behavioral health crises, which can include aggression, anxiety,

depression, panic attacks, irritability, non-suicidal self-injury, STB, and homicidal ideation, among other presentations. Information collected by this pediatric PES includes mental health symptoms, educational, social, and familial factors, demographics, admission information, diagnoses, insurance, housing status, and discharge disposition. Additionally, the dataset contained unstructured notes from an initial evaluation performed by a PES clinician.

Data Processing

The study dataset was limited to new and initial evaluations conducted by PES clinicians. Structured data retained for analyses included: hospital admissions, age, gender, race, ethnicity, housing status, insurance, and billing diagnoses. Most of the rich clinical symptomatology and information was contained in the initial evaluation note that has a semi-structured format. Rule-based information extraction methods were used as an initial step in obtaining pertinent features from the notes.^{404,405} Basic negation strategies were used in addition to excluding family history.^{406–409} PES clinicians assisted in identifying important areas of the note to extract and provided clinical context when needed. A large percentage of patients seen by PES in the ED come in for a reason of STB. One of the first steps to analyze patients presenting with a moderate to high level of suicide risk was to first identify those encounters in the dataset. The PES clinician experts confirmed that using solely billing diagnoses was not an accurate representation of those that presented with STB. The literature also states that identifying suicidal patients using diagnoses codes alone has challenges and limitations.^{410,411} A three-step protocol was produced alongside clinicians to accurately identify STB encounters in the dataset (**Table 7.1**). The first step was to check all diagnoses for any STB diagnoses (e.g., “suicidal ideation” or “suicide attempt”). The second and third steps checked areas of the note for moderate or high suicide risk level or active suicidal ideation. Patients with ASD were identified from the billing diagnoses, diagnoses listed in the encounter note, past medical history, problem list, and extracting the first sentence of the History of Present Illness (HPI).

Conditions were extracted from the structured and unstructured parts of the dataset to identify, explore, and report common conditions for the patients in each encounter. To further characterize clinical features of the

patients who presented with STB, sections of the PES initial evaluation note were extracted. Any section of the note that matched a set of regular expressions in either single select or multi-select options were considered for analysis. All sections and subsections of the note were transformed into binary features. **Table 7.2** provides an example of the sub-section, “Affect,” of the Mental Status Exam and the different drop-down options that were turned into binary features (1= present in the note; 0 = not present). **Figure 7.3** illustrates the note layout and a list of the sections and features extracted.

Table 7.1: Protocol for identifying encounters positive for STB.

Extract STB Info		Determine if Positive STB
1	• Billing Diagnoses • Primary/ Additional Diagnoses (Note)	• Check diagnoses for: “suicide*”, “suicidal*” = POSITIVE • If no matches: check # 2
2	• Suicide Risk Level (Note): High, Moderate, Low, N/A	• If High or Moderate = POSITIVE • If Low, N/A, or blank: check # 3
3	• Suicidal Ideation (Note): Active, Passive, Plan, Intent, Denies	• Active, Passive, Intent, or Plan = POSITIVE • If Denies, blank, etc. = NEGATIVE

Table 7.2: Example of note feature extraction (flat affect) transformed into binary variables for analysis.

Evaluation Note: Feature Example	
Section	Mental Status Exam
Subsection	Affect
Drop-down Select Options	Appropriate; Euthymic; Depressed.; Dysphoric; Labile; Expansive; Flat; Irritable; Blunted; Constricted; Mood congruent
Binary Feature	Affect – Flat → 1 = present; 0 = not present

Behavioral Health Pediatric Emergency Services Initial Evaluation Note Template	
Chief Complaint	Free Text
History of Present Illness	Free Text
Columbia Screen (C-SSRS)	Low Risk (0;5-1;5); Moderate Risk (2-4;5); High Risk (5+)
Risk Level	
Suicide Inquiry	
Suicidal Thoughts	Free Text
Suicide Plan (timing; location)	
Availability of Means	
Preparatory Acts/Behaviors	
Intent (lethality)	
Risk Behaviors: Past and Current Risk/Safety Assessment	
Aggressive/Assaultive	Not active and denies history Active; see HPI Active *** Not active Past *** Denies past history
Homicidal Ideation/Attempts	
Self-Injurious Behavior	
Sexualized Behavior	
Elopement	
Fire Setting	
Property Destruction	
Cruelty to Animals	
Pica/Swallowing objects	
Somatic Functioning	
Sleep	unremarkable; hypersomnia; insomnia; initial; middle; early awakening
Weight	no changes; loss 1-10 lbs; loss 10+ lbs; gain 1-10 lbs; gain 10+ lbs
Appetite	no change; increased; decreased
Eating Behaviors	unremarkable; restricting; bingeing; purging
Energy	developmentally appropriate; increased; decreased
Additional History	
Trauma History	sexual abuse; physical abuse; neglect; witnessed domestic violence; intimate partner violence; bullying; motor vehicle accident
Substance Use History	positive for any substance use
Family History	Separated list
Past Medical History	Separated list
Problem List	Separated list
Mental Status Examination	
Manner	Calm; Cooperative; Guarded; Hostile; Glib; Suspicious; Withdrawn; Inappropriately familiar; Seductive
Musculoskeletal	Gait and station normal; Abnormal tone; Tics; Tremors;
Motor	Unremarkable; Hypermotoric; Psychomotor agitation; Psychomotor retardation;
Affect	Appropriate; Euthymic; Depressed; Dysphoric; Labile; Expansive; Flat; Irritable; Blunted; Constricted; Mood congruent;
Thought Process	Linear; Nonlinear; Disorganized; Racing thoughts; Blocking; Slowed; Concrete; Logical; Illogical;
Thought Content	unremarkable; Worthlessness; Hopelessness; Guilt; Ideas of reference; Paranoid ideation; Delusions; Obsessions; Phobia;
Perception	No hallucinations; Command hallucinations; Auditory hallucinations; Visual hallucinations;
Suicidal Ideation	Denies; Passive; Active; Plan; No Plan; Intent; No Intent

Figure 7.3: Clinical initial evaluation note template: section headers, subsections, and the regular expression options for extraction.

Analysis & Evaluation

Descriptive statistics were generated to characterize the overall population and sub-groups: (1) all encounters, (2) ASD without STB, (3) ASD with STB, (4) Non-ASD without STB, and (5) Non-ASD with STB. Prevalence percentages for demographics, conditions, and extracted note features were calculated and compared for each subgroup of interest. The ASD (no STB) vs. ASD (STB), Non-ASD (no STB) vs. Non-ASD (STB), and ASD (STB) vs. Non-ASD (STB) subsets were statistically compared through use of the chi-square (χ^2) test and the p-values were reported.^{412,413} A subset of the important features analyzed are reported.

Supervised machine learning methods were explored to classify STB (1) or no STB (0), and model relationships between STB (label variable) and clinical presentation features (demographics, evaluation note features, and some past medical history conditions). Multiple machine learning models were explored and compared including Support Vector Machine, Gaussian Naïve Bayes, Random Forest, and XGBoost.⁴¹⁴ Support Vector Machine or Support Vector Classifier (SVC) is a discriminative classifier where the algorithm tries to find an optimal hyperplane that accurately separates observations into different categories in hyperspace. The Gaussian Naïve Bayes classifier is a probabilistic algorithm that internally uses Bayes Theorem. Random Forest is an ensemble learning-based algorithm that internally uses multiple decision trees to make the classification. XGBoost (Extreme Gradient Boosting) combines the predictions of multiple weak models to produce a stronger prediction.⁴¹⁵ XGBoost was specifically selected since Tree SHAP has been integrated into XGBoost for feature comparison and explainability. SHAP (Shapley Additive exPlanations) by Lundberg and Lee (2017) is a method to explain individual predictions and serves as a unified approach to explain the output of any machine learning model.⁴¹⁶ SHAP is based on the game theoretically optimal Shapley values. SHAP connects game theory with local explanations, representing the only possible consistent and locally accurate additive feature attribution method based on expectations.

The original data set was randomly partitioned into a training set (80%) and a hold-out testing set (20%). Model hyperparameters were optimized using random search. Model performance was evaluated using area

under the ROC curve (AUC) scores and k-fold cross validation on the training set with $k = 10$ folds. Testing set performance was evaluated on the originally held-out testing set. Several different feature importance methods were compared using Gini impurity and permutation-based methods. SHAP feature rankings and bee swarm plots were compared in the two separate models for ASD and Non-ASD subgroups so that important features unique to the ASD group could be identified.

7.4 Results

Descriptive Statistics

Data for patients presenting to the ED in behavioral health crisis and were referred to PES for a psychiatric risk evaluation were analyzed for an approximately three-year period (November 2019 – October 2022). Since there were no patients with ASD under the age of 4, an inclusion criterion of 4-17 years old was specified and any other ages were excluded so that the data for ASD and non-ASD could be properly compared. This study focused on encounter-level data as the main goal was to describe the clinical characteristics of individuals who present with STB at an ED encounter. It is worth noting, there is roughly a ~30% readmission rate for patients who come back to the ED for psychiatric services over the three-year study period. Therefore, some of the same patients are repeated in the encounter level data during the three-year period. Any counts less than 10 were redacted. There was a total of **6,350** encounters identified and analyzed for the total PES population. Out of all the encounters, **3,816 (60.1%)** were identified as visits presenting with STB. Patients with ASD were identified, and **997 (15.7%)** of all encounters were for individuals diagnosed with ASD. Out of the ASD cases, **442 (44.3%)** were for a reason of STB.

Table 7.3 describes the demographics (sex, age groups, race, ethnicity, and insurance), C-SSRS risk levels, and some common conditions seen in the ASD and STB groups of encounters. **Table 7.4** describes a subset of the initial evaluation encounter note features extracted that showed either some importance for STB encounters in general or some differences between those with ASD and without (Non-ASD). First, the full dataset is described (*All Encounters*) followed by each subgroup of interest. The subgroups were ASD

encounters with and without STB in addition to the encounters from the rest of the population (Non-ASD) with and without STB. In both **Table 7.3** and **Table 7.4**, three comparisons were made between each subgroup and the separate clinical features of interest using the chi-squared statistical test with the p-values reported in the tables.

For the full dataset, there was a larger percentage of female encounters (58.4%), and majority were White or Caucasian (64.7%) (**Table 7.3**). Age groups were split into ages at admission 4-8, 9-11, 12-14, and 15-17. About 80% of the encounters were patients over the age of 12. The ASD cases were largely male (~70%), but the female prevalence increased in the ASD (+STB) encounters from 22.2% female without STB to 40.3% female with STB. The ASD encounters with and without STB were compared and statistical differences were shown. Some of the differences that stood out as increased in the STB population included: older teen ages, increase in prevalence of bipolar disorder, depressive disorder, PTSD, anxiety, obsessive compulsive disorder (OCD), learning disorder, eating disorder, gender dysphoria, and obesity. The rest of the population (Non-ASD) was also compared against each other and showed some similar trends to the ASD subgroup for increase in prevalence of older age and certain conditions in the STB population. To explain and characterize the statistical differences seen between those with ASD to those without, the ASD (+STB) and Non-ASD (+STB) groups were compared to identify any differences between the two populations. **Table 7.3** and **Table 7.4** label a statistical difference as **(ASD)** if the patients with ASD shows a statistically larger prevalence than those without ASD and labeled as **(Non-ASD)** for the population without ASD showing a higher prevalence in each dichotomous feature comparison. There were significantly lower numbers of high C-SSRS scores in the population with ASD, which could be for multiple reasons including that the C-SSRS screening tool is more challenging to administer in individuals with ASD or the severity level of STB is lesser. Depressed mood and affect clinical presentations stand out as statistically higher in the Non-ASD group. Many other conditions showed a larger difference and higher prevalence in the patients with ASD including schizophrenia, anxiety, obsessive compulsive disorder (OCD), attention deficit/hyperactivity disorder (ADHD), and obesity.

Table 7.3: Prevalence of demographics, average C-SSRS scores, and important conditions for each subgroup of interest: All Encounters, ASD with and without STB, and Non-ASD with and without STB. Chi-square p-values are reported comparing ASD with and without STB, Non-ASD with and without STB, and ASD with STB versus Non-ASD with STB.

	All Visits	ASD (-STB)	ASD (+STB)	ASD (-STB) vs ASD (+STB)	Non ASD (-STB)	Non ASD (+STB)	Non-ASD (-STB) vs Non-ASD (+STB)	ASD (+STB) vs Non-ASD (+STB)
Total	6350	555	442		1979	3374		
	Prev (%)	Prev (%)	Prev (%)	X ² (p-value)	Prev (%)	Prev (%)	X ² p-value	X ² p-value
Sex								
Female	58.4	22.2	40.3	6.1E-10*↑	50.7	71.3	7.7E-52*↑	2.4E-39* Non-ASD
Male	41.5	77.7	59.5	6.0E-10*↓	49.3	28.6	4.5E-52*↓	4.5E-39* ASD
Race								
White or Caucasian	64.7	74.8	75.6	7.7E-01	61.5	63.5	1.3E-01	6.4E-07* ASD
Black or African American	11.6	11.5	7.5	3.1E-02*↓	14.5	10.4	9.3E-06*↓	5.2E-02
Asian	1.2	R	R	R	R	R	R	R
American Indian Alaska Native	0.5	R	R	R	R	R	R	R
Unknown/Other	22.1	12.6	15.6	1.7E-01	22.5	24.2	1.5E-01	5.6E-05* Non-ASD
Ethnicity								
Hispanic	23.2	17.3	17.0	8.9E-01	22.5	25.4	2.0E-02*↑	1.1E-04* Non-ASD
Age Groups								
4-8	6.5	10.6	3.9	6.1E-05*↓	12.4	2.7	1.8E-45*↓	1.7E-01
9-11	13.5	19.3	11.1	4.0E-04*↓	19.0	9.7	5.0E-22*↑	3.7E-01
12-14	38.1	37.1	37.1	1.0E+00	32.5	41.6	5.0E-11*↑	7.2E-02
15-17	41.9	33.0	48.0	1.5E-06*↑	36.1	46.0	1.3E-12*↑	4.4E-01
Insurance								
Private	50.2	47.0	55.0	1.3E-02*↑	45.3	53.0	6.8E-08*↑	4.3E-01
Medicaid	48.7	53.0	44.6	8.4E-03*↓	53.4	45.9	1.3E-07*↓	6.0E-01
Average C-SSRS Score								
0	17.9	33.2	8.8	5.3E-20*↓	34.9	6.6	4.4E-155*↓	8.8E-02
0.5-5.5	21.9	14.8	21.5	5.8E-03*↑	24.0	22.0	9.3E-02	8.2E-01
6.0-10.5	17.7	3.1	22.4	3.1E-21*↑	7.6	25.4	1.7E-58*↑	1.7E-01
> 11.0	22.8	2.0	29.9	9.9E-36*↑	4.4	36.1	2.9E-150*↑	1.0E-02* Non-ASD
Conditions								
Laceration/Abrasion/Contusion	11.8	7.2	10.4	7.4E-02	11.0	13.1	2.0E-02*↓	1.1E-01
Poisoning/Toxic Effect	6.5	1.6	4.8	4.1E-03*↑	2.1	10.1	5.4E-28*↑	2.8E-04* Non-ASD
Adjustment Disorder	44.5	62.0	42.5	9.7E-10*↓	55.5	35.5	4.2E-46*↓	3.9E-03* ASD
Conduct Disorder	6.0	10.5	6.1	1.5E-02*↓	7.0	4.7	3.7E-04*↓	2.0E-01
Bipolar	5.4	4.9	9.1	8.7E-03*↑	4.7	5.4	2.2E-01	2.2E-03* ASD
Psychotic/Schizophrenia	2.7	3.2	3.9	6.1E-01	2.9	2.3	1.4E-01	4.6E-02* ASD
Depressive Disorder	77.7	46.5	84.4	5.9E-35*↑	62.3	90.9	8.4E-143*↑	1.4E-05* Non-ASD
PTSD	27.9	17.5	26.0	1.1E-03*↑	29.3	29.0	7.8E-01	2.0E-01
Anxiety Disorder	69.0	68.7	83.7	4.2E-08*↑	57.6	73.8	8.7E-35*↑	6.5E-06* ASD
Oppositional Defiant Disorder	10.6	14.2	11.8	2.5E-01	14.2	7.7	1.5E-14*↓	2.9E-03* ASD
Obsessive Compulsive Disorder	5.4	11.4	14.0	2.0E-01	3.3	4.6	2.9E-02*↑	5.7E-16* ASD
ADHD	48.2	70.1	72.2	4.7E-01	53.4	38.4	1.2E-26*↓	9.8E-42* ASD
Learning Disorder	2.9	4.3	8.6	5.5E-03*↑	1.9	2.4	2.2E-01	2.8E-12* ASD
Intellectual Disability	4.1	22.9	8.1	4.1E-10*↓	2.1	1.6	2.4E-01	3.1E-17* ASD
Eating disorder	6.8	1.6	5.0	2.4E-03*↑	3.5	9.8	3.4E-17*↑	1.1E-03* Non-ASD
Gender dysphoria	4.9	2.2	6.1	1.4E-03*↑	2.0	6.9	1.6E-15*↑	5.2E-01
Migraines/Headaches	6.7	4.7	10.2	8.0E-04*↑	3.7	8.3	4.3E-11*↑	1.9E-01
Asthma	17.3	20.2	20.4	9.4E-01	16.4	17.0	5.6E-01	7.8E-02
Obesity	8.1	10.8	17.0	4.8E-03*↑	6.0	7.8	1.5E-02*↑	1.7E-10* ASD
Seizures/epilepsy	3.8	13.3	8.1	9.4E-03*↓	3.3	2.0	2.9E-03*↓	9.9E-14* ASD
Constipation	10.7	21.6	16.3	3.4E-02*↓	6.8	10.5	5.0E-06*↑	2.7E-04* ASD

All prevalence % calculated based on subgroup total (total counts in row 1); R = redacted due to count <10; * = statistical significance (p < 0.05);

↑ = increase in STB group; ↓ = decrease in STB group; ASD = increase in ASD group; Non-ASD = increase in Non-ASD group

Table 7.4: Prevalence of a selection of the features extracted from the initial evaluation clinician note for each subgroup of interest: All Visits, ASD with and without STB, and Non-ASD with and without STB. Chi-square p-values are reported comparing ASD with and without STB, Non-ASD with and without STB, and ASD with STB versus Non-ASD with STB.

	All Visits	ASD (- STB)	ASD (+STB)	ASD (-STB) vs ASD (+STB)	Non-ASD (-STB)	Non-ASD (+STB)	Non-ASD (-STB) vs Non-ASD (+STB)	ASD (+STB) vs Non-ASD (+STB)
Total (count)	6350	555	442		1979	3374		
	Prev (%)	Prev (%)	Prev (%)	X ² p-value	Prev (%)	Prev (%)	X ² p-value	X ² p-value
Somatic Functioning								
Sleep Disturbances	50.4	42.7	51.4	6.5E-03*↑	38.3	58.5	2.3E-46*↑	4.1E-03* Non-ASD
Weight Gain	12.2	16.9	17.4	8.4E-01	10.1	12.0	3.4E-02*↑	1.3E-03* ASD
Weight Loss	6.9	3.2	4.5	2.9E-01	5.4	8.8	4.0E-06*↑	2.2E-03* Non-ASD
Appetite - Decreased	25.7	8.7	21.3	1.5E-08*↑	16.2	34.6	1.2E-47*↑	2.0E-08* Non-ASD
Eating - Restricting	9.5	2.3	7.5	1.3E-04*↑	4.6	13.9	3.4E-27*↑	1.7E-04* Non-ASD
Eating - Binging	5.1	4.7	6.1	3.2E-01	3.2	6.1	5.3E-06*↑	9.6E-01
Energy - Decreased	37.3	12.6	39.1	3.3E-22*↑	17.8	52.5	7E-138*↑	1.4E-07* Non-ASD
History								
Trauma - Sexual Abuse	19.8	8.7	6.8	6.4E-08*↓	18.1	22.5	1.2E-04*↑	3.6E-01
Trauma - Physical Abuse	16.5	13.0	20.6	3.2E-02*↑	17.6	16.2	1.7E-01	3.7E-01
Trauma - Bullying	10.8	5.8	17.9	1.9E-07*↑	8.9	12.1	4.1E-04*↑	2.4E-02* ASD
Substance Use	19.4	3.8	15.8	1.1E-02*↑	18.1	24.2	1.7E-07*↑	1.8E-15* Non-ASD
Pica/Swallowing Objects	15.1	4.1	7.5	6.5E-02	1.5	1.0	1.6E-01	1.6E-18* ASD
Mental Status Exam								
Manner								
Guarded	18.8	17.3	22.0	6.5E-02	16.5	20.0	1.8E-03*↑	3.3E-01
Withdrawn	9.8	5.4	11.8	2.8E-04*↑	6.0	12.5	1.3E-14*↑	6.4E-01
Hostile	3.06	4.3	5.2	5.2E-01	3.3	2.4	6.5E-02	8.0E-04* ASD
Motor								
Psychomotor Retardation	2.1	1.3	4.8	9.2E-04*↑	1.0	2.6	5.2E-05*↑	8.4E-03* ASD
Affect								
Depressed	23.3	4.0	24.7	7.3E-22*↑	7.4	35.6	3E-116*↑	5.3E-06* Non-ASD
Dysphoric	4.2	2.7	4.8	8.5E-02	2.1	5.6	6.1E-10*↑	4.5E-01
Labile	2.9	4.3	6.3	1.6E-01	1.9	2.8	4.9E-02*↑	6.7E-05* ASD
Flat	11.8	8.3	18.1	3.6E-06*↑	6.6	14.5	2.9E-18*↑	4.7E-02* ASD
Irritable	12.1	16.6	17.2	8.0E-01	13.3	10.1	3.3E-04*↓	6.3E-06* ASD
Blunted	2.3	3.4	4.5	3.7E-01	1.3	2.5	4.2E-03*↑	1.2E-02* ASD
Constricted	13.6	13.7	19.0	2.3E-02*↑	10.0	15.1	8.5E-08*↑	3.2E-02* ASD
Thought Process								
Racing Thoughts	1.9	2.5	4.1	1.7E-01	1.4	1.8	3.1E-01	1.4E-03* ASD
Slowed	2.4	4.1	6.8	6.5E-02	1.5	2.1	1.1E-01	5.5E-09* ASD
Illogical	1.1	1.8	3.2	1.6E-01	0.9	0.8	7.6E-01	9.5E-06* ASD
Thought Content								
Worthlessness	25.6	3.1	32.8	1.2E-36*↑	5.4	40.3	1.1E-167*↑	2.6E-03* Non-ASD
Hopelessness	26.7	1.8	36.7	1.9E-47*↑	4.3	42.6	2.7E-197*↑	1.8E-02* Non-ASD
Guilt	17.7	8.7	20.4	1.0E-07*↑	8.6	24.1	1.5E-45*↑	8.0E-02
Paranoid	1.8	0.4	2.7	1.7E-03*↑	1.4	2.1	6.0E-02	3.8E-01
Obsessions	0.9	2.0	3.2	2.3E-01	0.5	0.7	3.6E-01	1.0E-06* ASD
Perception								
Command Hallucinations	2.1	0.7	4.8	5.3E-05*↑	0.6	2.8	3.3E-08*↑	2.3E-02* ASD
Auditory Hallucinations	5.8	4.0	11.1	1.4E-05*↑	2.9	7.2	3.2E-11*↑	3.9E-03* ASD
Visual Hallucinations	3.8	2.0	5.2	5.4E-03*↑	2.3	4.8	3.7E-06*↑	7.1E-01
Psychiatric Symptoms/Behaviors								
Depressed Mood	58.9	16.2	68.3	7.4E-63*↑	31.4	80.9	3.1E-286*↑	7.3E-10* Non-ASD
Psychotic	2.9	3.1	5.2	8.7E-02	2.0	3.2	1.3E-02*↑	2.7E-02* ASD
Hopeless	20.1	0.7	31.9	9.2E-44*↑	1.5	32.6	1.3E-159*↑	7.6E-01
Panic	33.0	24.5	38.9	1.0E-06*↑	23.3	39.3	4.1E-33*↑	8.8E-01
Elopement Risk								
Moderate/High	21.8	51.2	51.4	9.5E-01	40.5	33.2	6.0E-08*↓	5.2E-14* ASD

All prevalence % calculated based on subgroup total (total counts in row 1); R = redacted due to count <10; * = statistical significance (p < 0.05); ↑ = increase in STB group; ↓ = decrease in STB group; ASD = increase in ASD group; Non-ASD = increase in Non-ASD group

The note features seen in **Table 7.4** compare each subgroup of interest. Some features that showed statistically higher prevalence in both the ASD and Non-ASD groups that presented with STB include sleep disturbances, decreased appetite, decreased energy, abuse, substance use, depressed affect, worthlessness, hopelessness, hallucinations, and panic. Some noted statistical differences seen as higher prevalence in the ASD (+STB) compared to the Non-ASD (+STB) group included bullying, pica/swallowing objects, several different affect features (labile, flat, irritable, blunted, and constricted), abnormal thought process (racing thoughts, slowed, illogical), obsessions, command hallucinations, and auditory hallucinations. It is interesting to note that the Non-ASD (+STB) subgroup had a much larger prevalence of depressed mood and affect compared to the ASD (+STB) subgroup.

Supervised Learning Models & Feature Importance

Machine learning models for STB classification were generated for both the ASD subset and Non-ASD subset of the data. Several different models of interest were explored that included Gaussian Naïve Bayes, Support Vector Classifier, Random Forest, and XGBoost. Out of the 142 features extracted from the data, using the chi-square statistical comparisons from the statistical analysis in addition to clinical expertise, the models used 90 unique features that included a selection of the demographics, conditions, and clinical note features to classify STB. The receiver operating characteristic (ROC), area under the ROC Curve (AUC) scores, and confusion matrices are reported below.

Ten-fold cross-validation was performed and the ROC curves can be visualized in addition to the mean AUC of the validation set for each model and each subgroup in **Figure 7.4**. As seen by the mean AUC values, each model performed similarly with XGBoost having the highest validation set mean AUC of 0.851 for the ASD subset and 0.856 for the Non-ASD subset. XGBoost was chosen as a focus for the rest of the metrics since it performed the best and can generate SHAP plots for comparing feature importance and explainability. **Table 7.5** shows the AUCs for the XGBoost 10-fold cross-validation in addition to the mean and test set AUC. **Figure 7.4** also shows the ROC curve for the test set of the XGBoost model, which

had a mean AUC of 0.825 for the ASD subset and 0.840 for the non-ASD subset. **Tables 7.6 and 7.7** report the confusion matrices for each of the ASD and Non-ASD XGBoost model test sets.

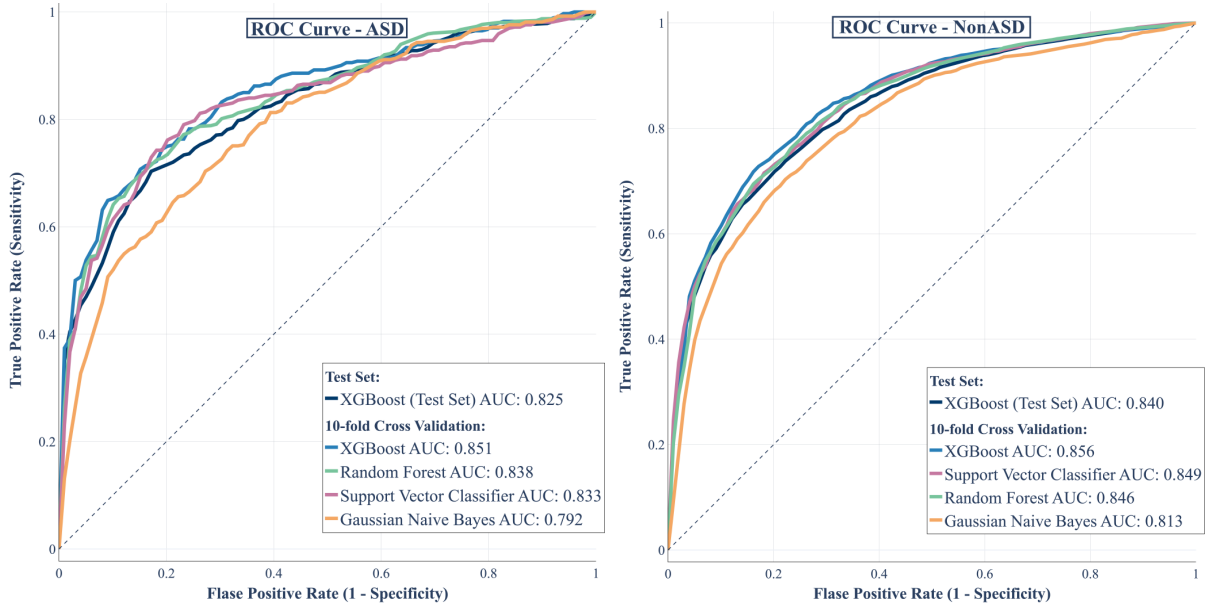


Figure 7.4: ROC curves for the ASD and Non-ASD subgroups of the dataset. The true positive rate (sensitivity) is plotted against the false positive rate ($1 - \text{specificity}$) comparing four separate models (XGBoost, SVC, Random Forest, and Naïve Bayes). The ROC curve for XGBoost test set, the best performing model, is also plotted.

Table 7.5: AUC metrics for XGBoost 10-fold cross-validation and test set for both ASD and Non-ASD subgroups.

XGBoost Metrics	10-Fold Cross-Validation (CV) AUCs	Mean CV AUC	Test Set AUC
ASD Model	0.830, 0.864, 0.801, 0.845, 0.838, 0.764, 0.857, 0.931, 0.922, 0.857	0.851	0.825
Non-ASD Model	0.826, 0.878, 0.873, 0.823, 0.866, 0.877, 0.859, 0.844, 0.882, 0.828	0.856	0.840

Table 7.6 & 7.7: Confusion matrices for the XGBoost model output with ASD on the left and Non-ASD on the right.

ASD XGBoost		Actual Values	
		STB	Not STB
Predicted Values	STB	0.320 True Positives	0.065 False Positives
	Not STB	0.125 False Negatives	0.490 True Negatives

Non-ASD XGBoost		Actual Values	
		STB	Not STB
Predicted Values	STB	0.522 True Positives	0.134 False Positives
	Not STB	0.108 False Negatives	0.236 True Negatives

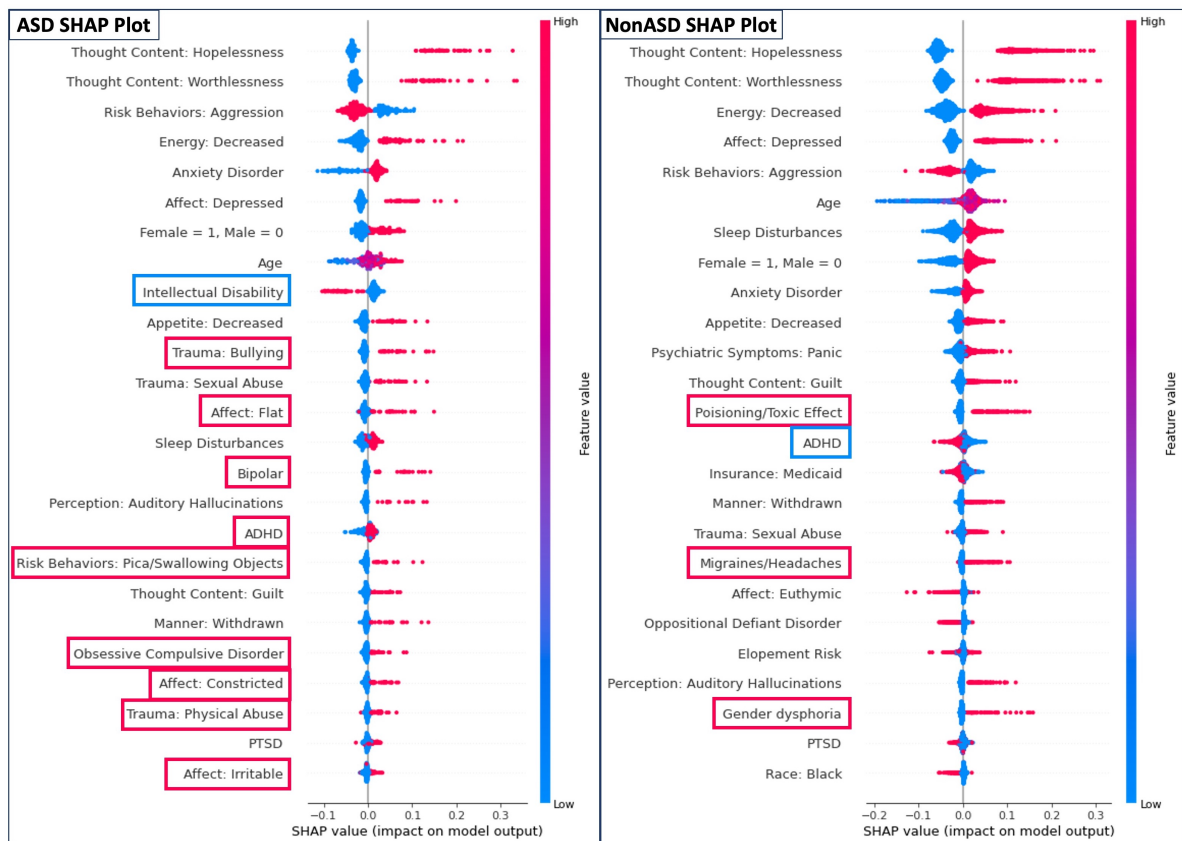


Figure 7.5: SHAP plots for the top 25 feature rankings to compare the differences between the ASD and Non-ASD models.

After determining a final model and selecting XGBoost as the model of interest, SHAP plots were generated and the top features for each model (ASD and Non-ASD) were compared. The top 25 SHAP feature rankings are compared in **Figure 7.5** to identify differences as having a high impact on each separate model. The top eight ranked features showed some similarities such as age, female gender, depressed affect, hopelessness, worthlessness, and anxiety. These made logical clinical sense that they would contribute to a strong risk factor for positive classification of STB in both groups. The remaining top ranked features showed many differences between the ASD and Non-ASD subgroups. The ASD group showed higher impact on the model in several key areas that included affect (flat, constricted, and irritable), trauma (bullying and physical abuse), pica/swallowing objects, bipolar disorder, and OCD. It was also observed that intellectual disability had a negative impact on the model (negative SHAP value)

as also seen with aggression and younger ages. The Non-ASD SHAP rankings showed higher impact on features such as incidence of poisoning/toxic effect (swallowing pills, alcohol toxicity, etc.), migraines/headaches, and gender dysphoria. ADHD had an opposite impact on the ASD versus Non-ASD model. It is clear that each of the models behave differently, and there are presentations and characteristics that are unique to the population with ASD.

7.5 Discussion

Little is known about the suicidal risk factors that are more prevalent or unique to the population with ASD. Due to communication challenges and other common ASD symptoms, it can be difficult to identify STB in these individuals. There is a need to improve understanding in how this patient population presents with STB to strive for early identification, diagnosis, and aid in the development of prevention interventions. In this study, retrospective EHR data including demographics, past medical history, and clinical features extracted from the PES clinician evaluation note were analyzed. The analyses aimed to characterize patients presenting to the ED for a chief complaint of STB and further explain differences seen in the patients with ASD. The goal was to then build predictive models of both the ASD encounters and a separate model of those without ASD and accurately classify patients as presenting for STB to the ED. Rankings of features using Shapley values were compared to describe differences and explain how each model may be behaving differently based on the two separate populations.

We validated that there is increasing statistically significant incidence of mental health and other conditions among the patients with ASD presenting to the ED in behavioral health crisis. This follows national trends of individuals with ASD, and since this was an acute or more severe population, the goal was to also describe some of the unique characteristics of patients with ASD presenting with STB. Some differences in the incidence rates of the extracted clinical features compared to those without ASD included higher rates of trauma, PTSD, abuse, bullying, acute stress, panic, irritability, hallucinations, and difficulty to express or read emotions due to mixed affect. On the other hand, individuals with ASD showed lower rates of depressed mood and depressed affect compared to the Non-ASD visits.

Models using a combination of different supervised machine learning methods were explored for ASD and Non-ASD. XGBoost performed the best with AUC and accuracy levels greater than 0.8 in both the ASD and Non-ASD groups. Since XGBoost can identify nonlinear relationships, this model was validated, and the SHAP summary plots of feature rankings were compared to identify differences and explain some of the model behaviors. Some of the higher ranked features that impacted the model output (or classification of STB) were consistently different in the individuals with ASD. These included affect, pica (or swallowing objects), physical abuse, bullying, hallucinations, and OCD. Affect needs further explanation so that unique questions or priority can be given to the trouble in expressing and describing emotions for those with ASD. This is supported in the literature and described as alexithymia (when a person has difficulty identifying and expressing emotions) as an important area of interest in STB and ASD research.⁴⁰² These other areas of focus such as trauma, bullying, and pica could flag the need for early intervention to prevent STB and demonstrates areas for needed resources of these significant mental health safety concerns.

Rich clinical data are often found in clinician notes, and this is especially true in the psychiatric field. This initial study used basic NLP approaches to extract information from the PES clinician evaluation notes. More advanced NLP methods and tools will be explored in the future to extract additional pertinent information in free text sections in addition to moving towards generalizing the work to be externally validated at other institutions that use different note templates. A limitation of this dataset was the high readmission rate (~30%) of the same patient seen two or more times during the three-year time frame. Since the study involved encounter-level analyses, it was not unusual for a patient to appear more than once in the dataset. Therefore, to ensure accurate evaluation of model performance, grouped k-fold cross validation was performed, with the “groups” corresponding to patients. This guaranteed that each patient (or group) appeared in exactly one-fold, and thus occurred exactly once in the validation set across all folds during the cross-validation process. This ensured that data from a single patient did not “bleed” across folds and artificially inflate the model performance. Another known limitation to note is in the interpretability of the nonlinear XGBoost “black box” model. SHAP summary plots (“beeswarm” plots) help interpret how the

model behaves and explain the output, but there are still challenges to making interpretations and linking to clinical significance.

Next steps include involving additional clinician experts in further validating findings and feature rankings. Future studies could look at patient-level data in addition to the longitudinal data of each patient to help address this limitation and understand how STB severity levels change over time for patients who return to the ED in crisis. As evident from the results, it can be difficult to determine suicide risk level and STB in individuals with ASD due to difficulty to express and read emotions among other factors. This work is a starting point to developing a more robust clinical prediction model that could assist clinicians in assessing and assigning suicide risk to individuals with ASD based on the factors found in the EHR and clinical evaluation note. A prediction model designed with different populations in mind can provide clinicians and support staff with more accurate suicide risk levels than the current screening tools available and assist in earlier intervention for these youth in behavioral crisis.

7.6 Conclusion

This study was an exploratory study that sought to characterize pediatric patients presenting to the psychiatric ED with STB. A two-phased approach was used that first statistically compared the important clinical features extracted from retrospective EHR data to further characterize pediatric patients with ASD versus the general pediatric population. A classification model was then built for each group so that feature rankings could be compared between the ASD cases to those without ASD. The results of this study indicated there were important differences in clinical characteristics of those with ASD compared with those without ASD who presented with STB. Clinical features that showed important impact in predicting high suicide risk in the ASD cases include elements of the mental status exam including affect, trauma symptoms, abuse history, and auditory hallucinations. Focused attention is needed on these unique differences in ASD cases so that suicide risk level can be appropriately and promptly addressed.

7.7 Acknowledgements

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Chapter 8: Aim 3-

Bridging Qualitative Insights and Computational Analyses to Address Autism Spectrum Disorder Needs with a Targeted Technological Intervention Prototype

List of Chapter Acronyms

ASD = Autism Spectrum Disorder

BD-LHS = Bridge to Discovery in Learning Health Systems

CFIR = Consolidated Framework for Implementation Research

ED = Emergency Department

EHR = Electronic Health Record

ERIC = Expert Recommendations for Implementing Change

HIE = Health Information Exchange

LHS = Learning Health Systems

pediPASS = Pediatric Portal to Access Safety & Services

RIPIN = Rhode Island Parent Information Network

SMART on FHIR = Substitutable Medical Applications, Reusable
Technologies on Fast Healthcare Interoperability Resources

STB = Suicidal Thoughts and Behaviors

Preface

Aim 3 serves as the synthesis of the research, integrating and interpreting the insights from both the qualitative discussions of Aim 1 (Chapter 3) and the computational analyses of Aim 2 (Chapters 4-7), to form an understanding of the findings and provide implications for next steps. This aim is designed to synthesize these findings to inform and propose a targeted technological intervention that addresses the identified gaps in support and resources for the Autism Spectrum Disorder (ASD) population. This synthesis is guided by the Bridge to Discovery in Learning Health Systems (BD-LHS) framework, which advocates for an integrative approach to knowledge discovery in healthcare. By combining the depth of qualitative understanding with the breadth of computational analyses, this work seeks to provide recommendations and guidance in the development of a targeted technological intervention. The process of integrating the qualitative and computational findings illuminates the specific needs and challenges faced

by this population and highlights the potential pathways for technology to enhance healthcare outcomes. Through this approach, this chapter culminates a concrete application of the BD-LHS framework, demonstrating its value in bridging disparate methods of research to foster continuous learning and improvement within the Learning Health System (LHS) paradigm.

8.1 Introduction

In the evolving landscape of healthcare, the adoption of mixed methods approaches in LHSs provide a strategy to bridge the gap between quantitative data and qualitative insights. This holistic approach enhances our understanding of complex health problems and catalyzes actionable change by integrating these diverse perspectives. By combining the analytical rigor of computational methods with the contextual richness of qualitative research, healthcare professionals can develop more effective interventions. These efforts allow for a better understanding of patient experiences, healthcare system inefficiencies, and health disparities, which can lead to more informed decision-making and improved health outcomes.

This chapter aims to synthesize the qualitative insights derived from focus groups with caregivers of high-needs children (*Chapter 1*) with the computational analysis of clinical data concerning the ASD population and the broader high-needs demographic within Rhode Island (*Chapters 4-7*). This synthesized knowledge highlights critical areas for support and intervention and paves the way for the design of a technological application, directly informed by the intersecting perspectives of caregivers and the quantitative findings from state-wide clinical data. This approach exemplifies the power of combining qualitative depth with quantitative breadth to craft interventions that are both evidence-based and deeply attuned to the lived experiences of families navigating the complexities of high-needs care. The integrated findings inform a concept and a digital tool tailored to the unique needs of high-needs children and their caregivers, facilitating mental health and safety management. This application aims to embody the principles of BD-LHS by leveraging integrated insights to create a practical, user-centered solution. Following this, an implementation strategy is proposed providing necessary next steps for successful development and implementation of the application.

BD-LHS Summary

The BD-LHS framework represents a mixed methods approach to knowledge discovery in healthcare. It aims to enhance the development and implementation of healthcare interventions within the broader LHS approach by synergistically integrating qualitative insights with computational findings^{57,60}. The concept of a LHS emphasizes the importance of continuous learning from healthcare data and systematically applying this knowledge to improve health outcomes. A key challenge within LHS is the effective integration of diverse methodologies for knowledge discovery. The BD-LHS framework proposes a solution to this challenge by combining qualitative insights and computational analytics, thus enhancing the development, implementation, and outcomes of healthcare interventions. It emphasizes the notion that merging computer-generated insights with human insight surpasses the potential of each individually. By bringing together these various methodologies, BD-LHS aims to better understand complex health problems. This helps create specific healthcare solutions that address the needs found in the research, leading to better health outcomes.

The methodological approach of the BD-LHS framework begins with qualitative insights, using methodologies such as needs assessments, user-centered design, and stakeholder analysis to understand the healthcare context deeply. This initial step ensures that interventions are grounded in the real experiences and needs of healthcare providers and patients. Concurrently, the framework employs computational methods to analyze clinical data, including statistical analyses, machine learning models, and predictive analytics, to offer a scalable, data-driven perspective on health challenges.

At its core, the BD-LHS framework integrates these qualitative and computational findings to foster a holistic understanding that promotes knowledge discovery beyond what could be achieved through individual methods. This integration identifies convergence and divergence areas, enriching the intervention development process with a robust evidence base. With insights from both qualitative and computational analyses, the framework guides the creation of targeted interventions, including solutions, prototypes, or minimum viable products, for effective implementation within healthcare settings. The final

phase involves implementing these interventions in clinical environments and evaluating their impact, thereby establishing a continuous feedback loop that enriches the LHS with new insights and fosters an ongoing cycle of learning and improvement⁵².

Application to Dissertation

This dissertation serves as a practical application of the BD-LHS framework, showcasing its utility in informing healthcare interventions through an integrated approach to knowledge discovery. The effort is structured around three aims:

Aim 1 focuses on gathering qualitative insights through focus groups with caregivers of children with high-needs, in collaboration with the Rhode Island Parent Information Network (RIPIN), to understand their experiences and needs.

Aim 2 employs computational methods to analyze clinical data related to ASD and the broader high-needs population in Rhode Island, leveraging health information exchange (HIE) data to characterize these groups quantitatively.

Aim 3 integrates findings from Aims 1 and 2, using both qualitative insights and computational findings to propose the development of the "pediPASS" application. This digital intervention aims to address the identified needs through a tailored, accessible platform for managing mental health and safety.

Figure 8.1 visually represents the BD-LHS framework, detailing the integration of Aims 1, 2, and 3. This visual aid demonstrates the framework's application in guiding the research process, from qualitative and computational data gathering to the synthesis of these findings in the design of a targeted technological intervention.

This chapter stands as the integrative bridge between qualitative insights (*Chapter 1*) and computational analyses (*Chapters 4-7*), embodying the BD-LHS framework's commitment to continuous learning and improvement in healthcare. By proposing the necessary requirements for a technologically driven solution,

the research aims to offer a scalable, adaptable model for supporting high-needs children and their families within LHS. This aim demonstrates the principle that the integration of diverse data sources and perspectives can drive innovation and improvement in healthcare, particularly for the most vulnerable populations. The goal is to address the immediate needs of these children and their caregivers and lay a foundation for broader applications of the BD-LHS framework in facilitating health system transformation.

Building on the BD-LHS framework, the next sections integrate insights from caregiver focus groups and clinical data analysis to provide suggestions and strategies to improve healthcare practice. This analysis compares, contrasts, and brings together the diverse datasets, explaining the implications of the merged data. By doing so, it highlights critical intersections and divergences, offering a better understanding of the challenges and needs identified. This comparison lays the groundwork for informed decisions on intervention strategies, ensuring they are deeply rooted in both statistical evidence and real-world experiences. This then leads to the design of a mock-up for the pediPASS mobile application. This digital tool aims to support high-needs children and their families by addressing identified care challenges. The app's concept is detailed, informed by both qualitative and quantitative findings, and an outline for an implementation strategy is described, focusing on practical application and effectiveness in managing mental health and safety.

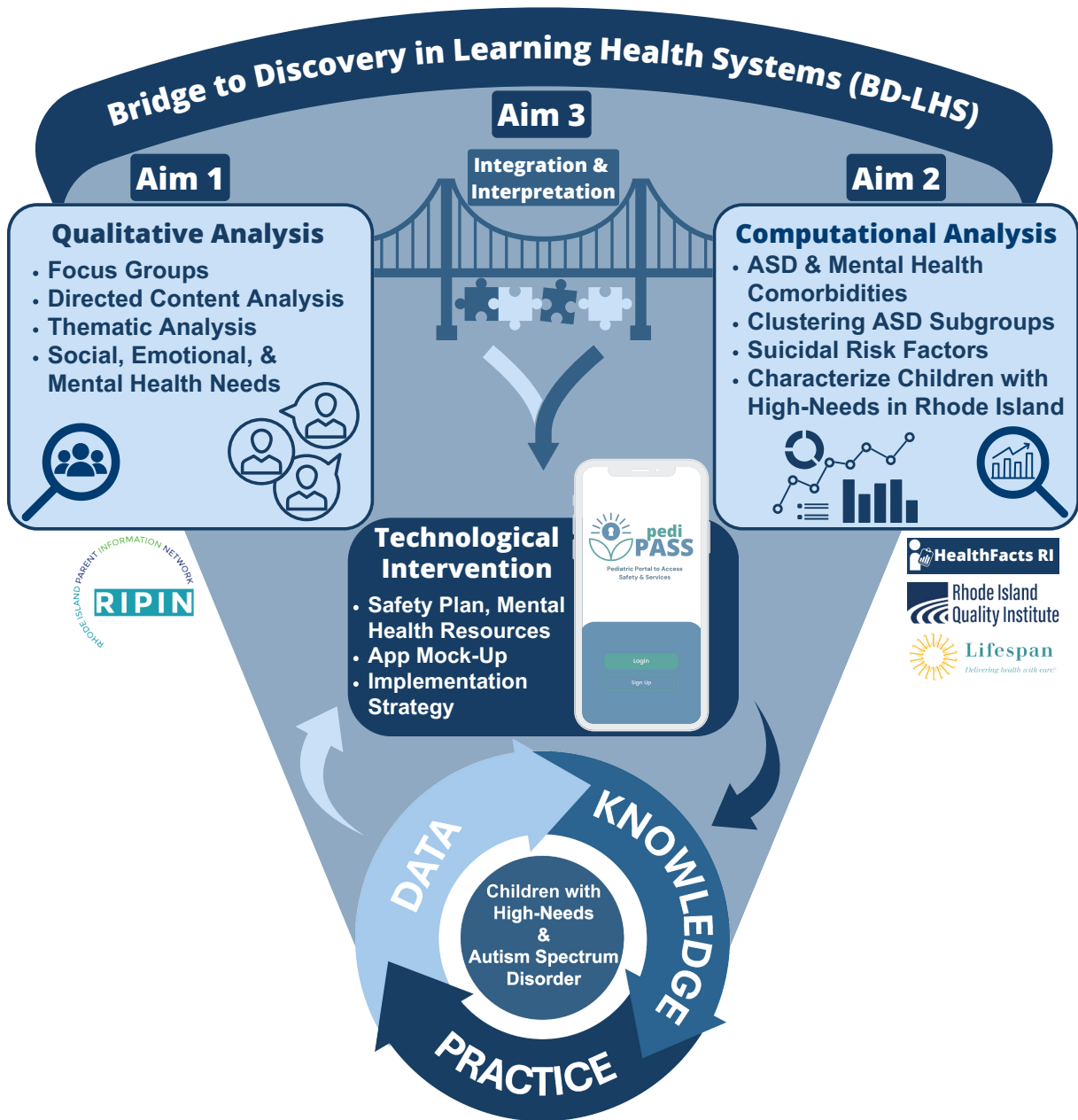


Figure 8.1: BD-LHS Framework Approach with Aims: Integrating Qualitative Insights with Computational Findings to Address the Needs of Children with High-Needs and ASD

8.2 Integration of Qualitative and Computational Findings

Introduction

To integrate the findings from the qualitative and computational findings in the previous studies, a structured approach is followed that highlights the convergence of insights gained from each method within the context of the BD-LHS framework. The findings are synthesized through descriptive analysis, using a comparison table, and constructing a joint display to illustrate the complex interplay between the lived experiences of caregivers and the computational analysis of clinical data^{129,144}. This integration serves as a foundation for formulating the next steps toward developing a tailored technological intervention. It highlights the key areas of need and potential intervention points that a technological solution could address, grounding the approach in both empirical evidence and real-world applicability^{417,418}. By merging experiences captured through focus groups with findings from statewide health data, this phase aims to distill an understanding of the unique challenges and needs faced by the high-needs population with particular emphasis on ASD.

The integration of these findings is crucial for several reasons. Firstly, it allows for a multi-dimensional view of the challenges and needs faced by high-needs children and their families, transcending the limitations of single-method studies⁴¹⁹. By combining the depth of qualitative narratives with the breadth of quantitative analysis, this section aims to highlight patterns and discrepancies that may not be evident when these datasets are considered in isolation. Secondly, this integrated approach facilitates the identification of targeted areas for intervention, directly informing the development of a technological application. The combination of qualitative and quantitative data provides a rich evidence base from which to design features that are responsive to the specific needs identified through caregiver narratives and reflective of broader population-level trends and needs. Furthermore, this integration demonstrates the application of the BD-LHS framework, illustrating its potential to enhance healthcare outcomes through a holistic and inclusive approach to data analysis. This section serves as a testament to the value of integrating diverse data sources and as a model for future research within LHS, emphasizing the importance of multi-

faceted perspectives in healthcare innovation. These integrated findings set the foundation for an evidence-based and user-centered approach to developing technological interventions aimed at improving the lives of high-needs children and their caregivers in Rhode Island. It exemplifies the synergy between qualitative insights and computational analytics, driving forward the mission to deliver meaningful, impactful healthcare solutions.

Methods

The integration of qualitative insights and computational analysis within the BD-LHS framework through summary of the disparate findings, parallel data analysis, comparison tables, and joint displays¹²⁸. This synthesis ensures the development of insightful and evidence-based interventions and demonstrates the practical applications of integrating diverse data types. The methodology outlined in this section emphasizes the importance of a cohesive strategy that respects the strengths and limitations of both qualitative and computational research, thereby contributing to the advancement of knowledge and the creation of unique solutions to complex health challenges and research questions^{420,421}.

Narrative Discussion

The narrative discussion serves as the backbone for integrating qualitative insights with computational analysis. This approach involves an examination of how findings from methodologies either support or conflict with one another, and how they collectively contribute to a more nuanced understanding of the research problem⁴²². The narrative discussion starts by summarizing the disparate studies. The narrative discussion is structured to dissect each finding, identifying the implications and potential applications of the data. This method allows for an in-depth exploration of the data, facilitating an understanding that might remain obscured without such integrative analysis^{117,145}.

Parallel Data Analysis

Parallel data analysis leverages the strengths of both qualitative and quantitative methodologies, providing a multi-layered understanding of complex research questions¹⁴⁴. This approach ensures that the depth and

context provided by qualitative data are balanced with the generalizability and precision of quantitative data. It is an independent analysis of each data type, preserving their unique contributions while maintaining a balanced perspective¹³⁰. Key steps include the independent analysis of data, identification of themes and patterns, cross-data analysis for convergence and divergence, and the final synthesis of findings into a unified narrative¹²⁸. By integrating these insights, parallel data analysis enriches the research with a multi-dimensional understanding, validating findings across methodologies, and enhancing the development of evidence-based interventions. The process of parallel data analysis aims towards a rigorous, interdisciplinary approach to address complex health issues and inform the design of evidence-based, user-centered technological interventions⁴²³.

Comparison Tables

Comparison tables are used to systematically juxtapose qualitative and quantitative findings according to predetermined themes or research questions⁴²⁴. This structured approach facilitates a clear, side-by-side evaluation of results from various data sources, highlighting areas of agreement, contradiction, or gap in the existing knowledge¹⁴⁶. By organizing data in this manner, the dissertation identifies critical points of convergence and divergence, which are instrumental to guide subsequent phases of investigation and intervention development. These tables serve as a visual and analytical tool to succinctly present and compare data, enabling researchers and stakeholders to quickly grasp the key findings and their implications.

Joint Displays

Joint displays are employed as a visual method to integrate and compare qualitative and quantitative findings^{130,425}. These visual representations are designed to promote a direct comparison, contrast, and synthesis of the data, thereby facilitating a deeper understanding of the health issue under investigation. Joint displays help in uncovering patterns, relationships, and discrepancies between datasets, offering a unique insight into the complexities of the research problem⁴²⁶. By visually merging data from different

methodologies, these displays enhance interpretive comprehension, allowing for an immediate and intuitive grasp of the integrated findings. This method is effective in illustrating the multidimensional aspects of the health issue, thereby enriching the analysis, and supporting the development of targeted technological interventions.

Results

Summary of Qualitative Findings

The qualitative findings from Chapter 3 (Aim 1), as part of a directed content analysis based on focus group discussions with caregivers of high-needs children, including those with ASD, revealed significant insights into the challenges faced by these families during the COVID-19 pandemic. The thematic analysis led to six primary themes that encapsulate the caregivers' experiences. These themes highlight critical areas such as the pressing need for essential support and access to services that extend beyond pandemic-related concerns, underscoring the systemic gaps in healthcare and specialized service accessibility for high-needs children.

Mental health emerged as a significant concern, with caregivers emphasizing the exacerbation of mental health issues and the lack of accessible, tailored mental health services. The pandemic's contribution to increased social isolation has notably impacted the emotional development and social skills of children, particularly those with ASD, leading to observed regressions in behavior and coping mechanisms. This situation emphasizes the necessity social support systems and resources aimed at mitigating isolation effects. Moreover, the analysis pointed out the need for resources and education on available services and mental health therapies. Caregivers expressed frustration over barriers to accessing crucial COVID-19 health services, including testing and vaccinations, which are compounded by the challenges specific to managing the needs of children with ASD. These barriers include logistical hurdles, emotional strain, and systemic obstacles that complicate access to timely and appropriate care.

To overcome these challenges, the findings suggest several pathways, including the development of targeted outreach programs to improve caregivers' awareness and access to specialized services. There is a clear call for the implementation of tailored mental health interventions that cater specifically to the needs of high-needs families, emphasizing the importance of integrating these services within existing healthcare frameworks to ensure accessibility. Additionally, enhancing community support mechanisms to address social isolation and fostering environments that encourage social engagement for children with ASD are vital steps towards mitigating the pandemic's adverse effects on this vulnerable population.

Overall, the qualitative analysis under Aim 1 sheds light on the challenges faced by caregivers of children with ASD and other high-needs conditions and outlines actionable recommendations for healthcare providers, policymakers, and community organizations to improve support structures and service delivery for these families.

Summary of Computational Findings

Chapter 4 (Aim 2a) sought to quantitatively characterize the high-needs pediatric population in Rhode Island through the analysis of statewide HIE data. This population comprises children with a wide array of conditions that necessitate specialized care, including but not limited to physical disabilities, developmental disorders, sensory impairments, intellectual disabilities, emotional and behavioral disorders, chronic health conditions, neurological disorders, mental health conditions, and medically fragile children, as well as children in foster care or with unstable living situations. The analysis aimed to provide an overview of the common conditions falling under "high-needs", illuminating the prevalence and distribution of various conditions, and thereby offering a better understanding of the population's healthcare requirements. This endeavor was crucial for several reasons: it provided an overview of the population, contributed insights into the experiences of caregivers, identified potential gaps in healthcare services and resources, laid a critical foundation for the design and proposal of technological interventions, and informed evidence-based policy and program development. Six broad diagnostic categories were identified: (1) Chronic Conditions/Medically Fragile, (2) Developmental Disorders, (3) Emotional & Behavioral Disorders,

(4) Mental Health Disorders, (5) Neurological & Neuromuscular Disorders, and (6) Sensory Impairments. This characterization of high-needs conditions using HIE data deepens the understanding of the diverse and complex healthcare landscape navigated by these children and emphasizes the necessity for healthcare systems to accommodate a wide spectrum of chronic and complex conditions. It highlights the importance of specialized services and resources in addition to the need for a collaborative care approach.

Chapter 5 (Aim 2b) focused on analyzing the comorbid mental health conditions among pediatric patients diagnosed with ASD within Rhode Island. Using the Rhode Island All-Payer Claims Database, the study employed descriptive statistics, association rule mining (ARM), and sequential pattern mining (SPM) to explore and characterize the comorbidity patterns associated with ASD patients. This analysis provided insights into mental health conditions accompanying ASD, emphasizing the need for targeted attention towards specific mental health issues. This study specifically focused on identifying prevalent mental health conditions co-occurring with ASD through advanced data mining techniques, revealing significant insights into the patterns and sequences of these comorbidities. The findings highlighted the importance of targeted interventions and research into specific mental health issues like suicidal ideation, mood disorders, anxiety, and conduct disorders among the ASD pediatric population.

Chapter 6 (Aim 2c) provided an in-depth exploration of ASD and its co-occurring conditions through a data-driven study, using HIE data. Employing data mining and clustering methods, the study identified distinct clusters within the pediatric population diagnosed with ASD, aiming to highlight demographic characteristics, healthcare utilization, and the prevalence of comorbid conditions, particularly focusing on mental health disorders. ASD, known for its complex neurodevelopmental challenges, was shown to co-occur with a higher prevalence of mental health issues such as anxiety, depression, ADHD, alongside sleep disturbances and gastrointestinal problems, than in the general pediatric population. This analysis revealed four groups within the ASD population, each with unique comorbidity profiles, underscoring the heterogeneity within ASD and emphasizing the need for tailored care strategies. The findings confirmed the heightened burden of co-occurring conditions and mental health diagnoses in individuals with ASD and

advocated for a multidisciplinary approach to care, integrating various specialties to effectively address the multifaceted needs of those with ASD. This analysis revealed distinct clusters, indicating varying levels of risk and comorbidities associated with ASD. Such detailed clustering offers insights into the broad spectrum of ASD, emphasizing the importance of personalized approaches to treatment and intervention based on specific profiles identified through health data analysis.

Chapter 7 (Aim 2d) focused on evaluating the psychiatric emergency services encounters for pediatric patients with ASD, specifically looking into those presenting with suicidal thoughts and behaviors (STB). Through a detailed analysis of encounter-level data from the emergency department, the research provided profound insights into the complexities of managing ASD patients in behavioral crises. A finding from this study was the identification of a diverse range of clinical characteristics that differentiated ASD patients with STB from those without, as well as from non-ASD patients presenting similar behaviors. Among these characteristics, certain mental health conditions, such as bipolar disorder, depressive disorders, PTSD, anxiety, and OCD, were notably more prevalent in the ASD population with STB, highlighting the interplay between ASD and other psychiatric conditions. Furthermore, the research emphasized the challenges in using traditional screening tools like the Columbia-Suicide Severity Rating Scale (C-SSRS) for ASD patients, suggesting the need for adapted or alternative approaches to accurately assess the risk of STB in this group. The analysis also pointed to specific symptoms and behaviors, including issues related to somatic functioning, history of trauma, and various psychiatric symptoms, that were more commonly observed in the ASD group with STB, indicating potential areas for targeted intervention. The findings from this study have important implications for clinical practice. They call for an understanding of the psychiatric needs of ASD patients, emphasizing the necessity for tailored approaches to assessment and intervention that consider the unique challenges faced by this population. Healthcare providers working in emergency and psychiatric settings need to be equipped with the knowledge and tools to effectively identify and address the complex mental health issues prevalent among ASD patients, particularly those at risk for STB. This might include specialized training, the development of adapted screening methodologies, and

the implementation of multidisciplinary care strategies that can adequately respond to the multifaceted needs of these patients.

Parallel Data Analysis

The parallel data analysis to integrate the disparate studies focuses on the high-needs pediatric population with a particular emphasis on individuals with ASD. It leverages both qualitative and computational approaches to address the challenges and needs of this vulnerable group, especially in the context of heightened mental health concerns, access to healthcare services, and the overall impact of the pandemic. Considering these findings in parallel allows for a layered understanding of the ASD population within the high-needs group. On one hand, qualitative findings offer a detailed exploration of the lived experiences of individuals with ASD and their families, highlighting the personalized challenges they face. On the other hand, quantitative data provides a macroscopic view of the ASD population, identifying key trends such as increased healthcare utilization, which indicates a pressing need for more accessible and tailored healthcare services. This dual approach corroborates the heightened mental health concerns voiced by caregivers and also points to systemic barriers in healthcare access and delivery.

The qualitative component, primarily through focus groups and thematic analysis, delved into the experiences of caregivers and individuals with ASD. It shed light on the complex and often overlooked aspects of living with ASD, such as the social and emotional ramifications of the pandemic, barriers to accessing essential services, and the acute need for mental health resources. Caregivers' narratives revealed a landscape marked by anxiety, stress, and a profound sense of isolation—emotions that are exacerbated by the pandemic but are endemic to the ASD experience. Simultaneously, the quantitative analysis employed computational methods to examine the broader patterns and trends within the high-needs population, with a special focus on ASD. This approach yielded critical insights into the prevalence of comorbidities among individuals with ASD, illustrating a burden that surpasses that found in the general population. These studies found higher rates of almost all mental health conditions including anxiety, depression, suicidal thoughts and behaviors, among other mental health disorders for individuals with ASD. This aligns with

the qualitative reports from caregivers about their children's mental health struggles. The computational findings also found a notably high rate of children with ASD presenting in psychiatric ED due to suicidality. The study highlighted that these children exhibit risk factors distinct from those in the broader population, pinpointing a pressing need for targeted identification of these risks. Importantly, it corroborates caregiver testimonies on the dire need for specialized mental health resources tailored to the unique needs of children with ASD, emphasizing the necessity for enhanced support and education for families navigating these challenges. Increased utilization of healthcare services by the high-needs and ASD populations underscores a paradoxical situation where demand for services does not equate to timely or effective care, often due to long wait times and a lack of specialized resources. This increased healthcare system use, as revealed by the computational analyses, signals a pressing need to address access issues and to tailor care more effectively to meet the unique needs of this population. The data points to an escalating concern among caregivers to enhance access to services and improve the quality of personalized care for these vulnerable populations. The convergence of increased healthcare utilization and reported mental health comorbidities highlights the critical gaps in the current healthcare system's capacity to provide for the complex needs of the ASD population.

The synthesis of qualitative and quantitative insights highlights the urgency of developing targeted interventions that address the complex needs of the high-needs population, particularly those with ASD. These interventions must be multifaceted, aiming to reduce the comorbidity burden by providing accessible mental health support and improving healthcare service delivery to mitigate the need for emergency care and hospital admissions. Furthermore, the findings advocate for a personalized approach to care, emphasizing the importance of understanding individual experiences and needs within the broader epidemiological trends. This could involve creating more adaptive healthcare systems that can swiftly respond to the nuanced needs of individuals with ASD, ensuring that mental health resources are available and tailored to address the specific challenges highlighted through both qualitative and quantitative research. The parallel data analysis, through its examination of both individual experiences and population-

level trends, illuminates the multifaceted challenges faced by the high-needs population, with a significant focus on ASD. By integrating these disparate yet complementary insights, the research lays a solid foundation for the development of nuanced, evidence-based interventions that can significantly improve the lives of individuals with ASD and their families, particularly in navigating the exacerbated challenges posed by the pandemic and beyond. This approach exemplifies the power of mixed methods research in driving impactful health and social care improvements for vulnerable populations.

Comparison Table

The integrated analysis now focuses solely on ASD, shifting its lens from the broader high-needs population to specifically address the unique challenges and needs within the ASD community. The comparison table (**Table 8.1**) below synthesizes findings from qualitative and computational studies, revealing critical areas in ASD care. It highlights the challenges caregivers face in accessing mental health services, corroborated by the high prevalence of mental health comorbidities like anxiety, depression, and ADHD in ASD children. The table also addresses the heightened risk of suicidality, emphasizing the need for specialized mental health resources. Indirectly supported by quantitative data, concerns over social isolation and its impact on mental health underscore the need for community-based programs. Additionally, the table illustrates systemic barriers in accessing specialized healthcare, advocating for enhanced navigation support and educational resources for caregivers, informed by the diverse healthcare needs of the high-needs pediatric population.

Joint Display

This section introduces a joint display that visually synthesizes all findings into a singular visualization highlighting the core insights. This approach to data synthesis is particularly effective in presenting complex information in an accessible manner. For this integrated analysis, an infographic was designed as the unified display to convey the combined findings in a clear and engaging format⁴²⁷. The infographic, titled "Navigating Autism and Mental Health: Insights from Data and Caregivers in Rhode Island" (**Figure 8.2**),

brings together key points from both caregiver experiences and computational data analyses to illuminate the multifaceted challenges and needs of the ASD community. It highlights the prevalence of mental health issues, emphasizes the barriers to accessing necessary services, and outlines the specific risk factors contributing to increased suicidality observed in the ASD population. By merging quantitative and qualitative insights, the infographic presents an overview of the ASD and pediatric mental health landscape in Rhode Island, offering invaluable insights for healthcare professionals, policymakers, and caregivers in tackling these pressing issues.

The infographic's top left quadrant, derived from Rhode Island's medical claims data (Chapter 5), illustrates a rising trend in ASD prevalence. The top right quadrant compares prevalence of health conditions between ASD and the broader pediatric population, using HIE data from the state, to spotlight the greater comorbidity burden in individuals with ASD, signaling an urgent need for specialized healthcare services (Chapter 6). The "Suicidal Risk Factors and Warning Signs" segment emphasizes critical findings related to suicidal ideation and behaviors among ASD individuals presenting to the emergency department during a behavioral health crisis (Chapter 7). These identified risk factors and warning signs in the ASD population highlight the importance of proactive care and intervention measures. The "Voice of Caregivers" portion features representative quotes and a word cloud from focus group participants, who indicate their child has ASD (Chapter 3). Predominant terms such as "access," "resources," "school," "services," "therapy," "struggle," "depressed," and "regressed" mirror the sentiments expressed, highlighting the demand for mental health services alongside the significance of emotional well-being and social interaction. The infographic concludes by advocating strategic recommendations for healthcare practices, including the development of customized mental health programs, enhanced access to specialized services, family-centered technological interventions, and crisis management resources for suicide prevention.

Table 8.1: Comparison Table of ASD-Related Challenges: Integrating Qualitative Narratives and Computational Data Insights

Condition/Challenge	Qualitative Findings (Aim 1)	Computational Findings (Aim 2)	Integrated Insights	Implications for Practice
Mental Health Comorbidities in ASD	Caregivers reported significant challenges in accessing mental health services for their children with ASD.	High prevalence of anxiety, depression, and ADHD identified among children with ASD.	The caregiver experiences align with the statistical prevalence, underscoring the urgent need for accessible mental health services for ASD patients.	Develop tailored mental health programs for children with ASD, considering both the caregivers' perspectives and the statistical prevalence of specific comorbidities.
Anxiety	Expressed concerns over anxiety management and its impact	Notably higher in ASD population.	Correlation between caregiver concerns and computational findings, urgent need for targeted anxiety interventions for this group.	Implement targeted anxiety management programs; increase caregiver support
Suicidal Thoughts and Behaviors (STB)	While not directly covered in Aim 1's caregiver narratives, some caregivers focused on declining mental health of their children and problems with depression and self-injurious behaviors.	Aim 2 highlighted an increased risk of STB among pediatric patients with ASD, noting specific mental health conditions prevalent in this group.	Although STB wasn't a specific focus in the qualitative findings, the quantitative evidence of STB among ASD patients identifies a critical area for attention especially with caregivers noting declines in mental health and lack of coping skills.	Prioritize screening for STB in pediatric patients with ASD and ensure mental health interventions are accessible and tailored to the ASD population's unique needs.
Social Isolation	Caregivers expressed concerns over the impact of social isolation on their children's emotional and social development.	Quantitative data did not directly measure social isolation but indicated high rates of conditions (e.g., anxiety) that could be exacerbated by isolation.	The qualitative concerns about social isolation find indirect support in the quantitative prevalence of related mental health conditions, highlighting a complex interplay between social factors and mental health.	Implement community-based programs and social skills groups to address the social needs of high-needs children, potentially mitigating the mental health impacts of isolation.
Access to Specialized Healthcare Services	Caregivers highlighted difficulties in navigating and accessing healthcare services for high-needs children.	Analysis identified a broad spectrum of conditions within the high-needs pediatric population, indicating diverse healthcare needs and specialized healthcare requirements.	Qualitative experiences of navigational challenges are supported by the quantitative evidence of a wide range of healthcare needs, suggesting systemic barriers to care.	Enhance healthcare navigation support and implement policies to streamline access to specialized care for high-needs populations. Provide education on how to access services and enhance communication between interdisciplinary teams.
Educational and Support Resources	Caregivers indicated a lack of adequate information and support resources for managing their children's conditions.	While quantitative studies focused on clinical aspects, the need for resources can be inferred from the identified high prevalence rates of complex conditions requiring comprehensive care.	Integrating the qualitative need for more resources with the quantitative evidence of complex care needs highlights a gap in caregiver support and education.	Develop and disseminate educational materials and support programs targeted at caregivers of high-needs children, informed by the range of conditions and challenges identified through research.

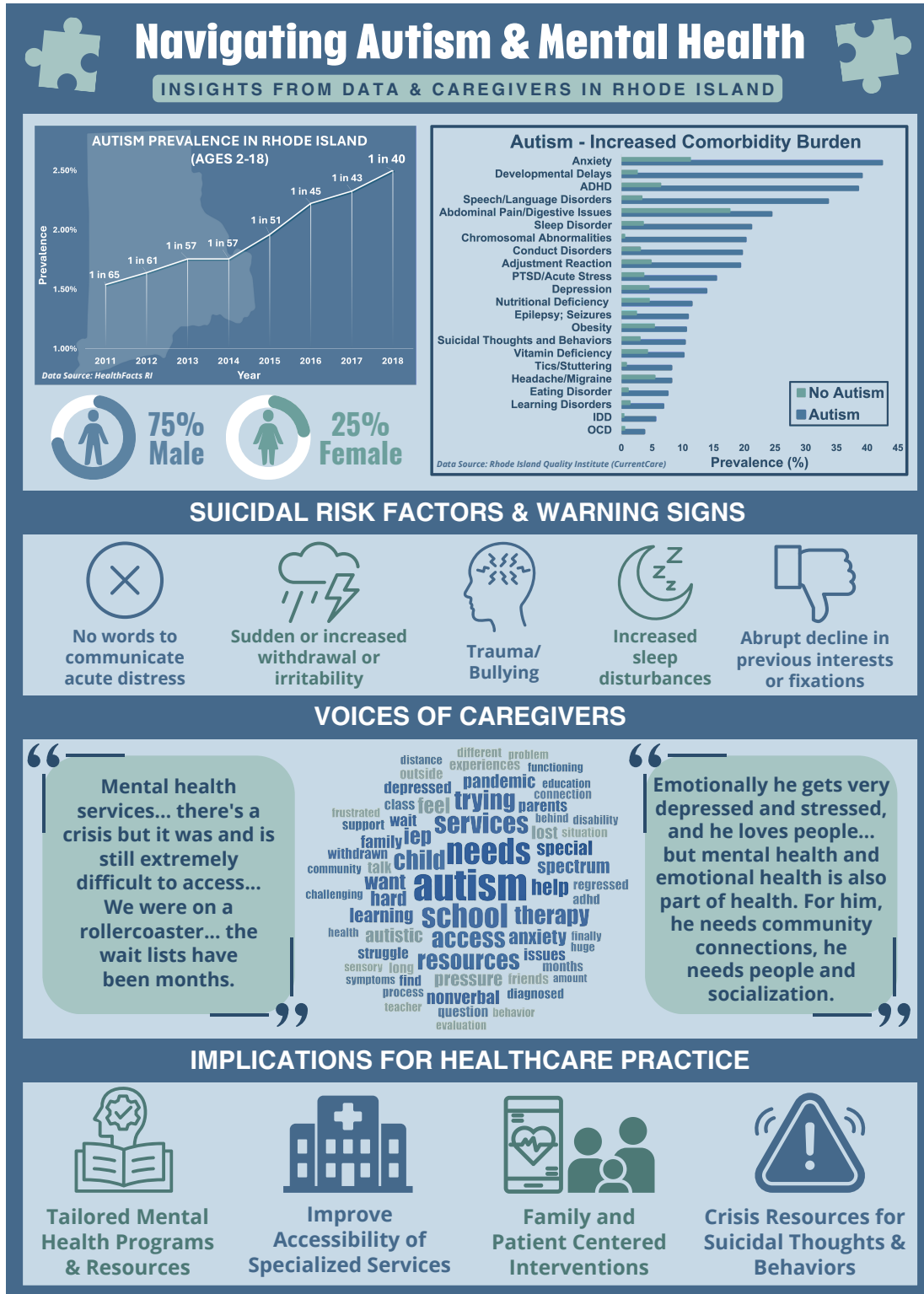


Figure 8.2: Navigating Autism and Mental Health—Joint Display Infographic and Visual Compilation of Data and Caregiver Insights in Rhode Island

Conclusion

The combined insights from the mixed methods study call for a strategy to address the needs of high-needs children and their families. Healthcare providers, policymakers, and support organizations should consider implications for practice described in **Table 8.2**.

Table 8.2: *Integrating Mixed Methods Insights for Enhanced Healthcare Practices*

Implications for Practice	Goal	Justification
Tailored Mental Health Programs & Resources	Develop interventions for ASD-specific challenges.	Address high incidence of mental health comorbidities in ASD and caregivers concerns for declining mental well-being.
Specialized Care Access	Improve availability and accessibility of specialized services.	Quantitative data shows diverse healthcare needs in high-needs populations.
Family and Patient Centered Interventions	Implement support that includes the family's role.	Qualitative findings highlight the family's impact on social and emotional well-being, and quantitative findings show a need for tailored interventions to improve mental health outcomes.
Crisis Resources for ASD and suicidal thoughts and behaviors	Provide accessible crisis management resources.	Increased risk of suicidal thoughts and behaviors in ASD individuals necessitates targeted crisis support.

The integration of qualitative insights from caregivers and quantitative computational findings has illuminated the multifaceted challenges faced by children with high-needs, particularly regarding mental health concerns like suicidal thoughts and behaviors. This understanding has paved the way towards actionable changes in practice and using this knowledge to inform technological interventions. The view provided by this research synthesis enhances the development of support systems that are both proactive and responsive. It suggests a model for healthcare that is data-informed, caregiver-sensitive, and tailored to the complex needs of the ASD population. Going forward, the findings advocate for continuous integration of diverse data sources to refine and evolve the support and resources available to children with high-needs, ensuring that interventions are effective, equitable, and accessible.

8.3 Technological Intervention

Introduction

The integrated findings lead to the conceptualization of a tailored technological intervention in the form of a digital tool for use by patients and caregivers. In this section, the concept and mockup of an application (“app”) is presented, illustrating the practical application of the research findings into a tangible solution. This demonstrates how the BD-LHS framework can be operationalized through the development of digital tools. This mockup serves as a visual and feature representation of how the app could operate, offering stakeholders a clearer understanding of its potential impact and utility in addressing the complex challenges identified through the integrated research approach^{428,429}. By adhering to the principles of the BD-LHS framework, the integrated findings showcase how synthesis between computational analyses and personalized health insights drive the creation of effective health interventions tailored for vulnerable populations.

In response to the identified needs, the development of "Pediatric Portal to Access Safety & Services (pediPASS)," a digital app tailored for children with high-needs and their caregivers, is proposed. This app aims to provide a dynamic, accessible platform for managing mental health and safety, incorporating features such as tailored safety plans, contact lists for crisis management, self-care checklists, and resources tailored to specific diagnoses like ASD. The proposal includes a prototype mock-up with the core components, requirements, and a detailed representation, providing a visual idea of what the app could look like. The prototype showcases its potential to serve as a critical resource for families and patients. The development and design of a technological solution is derived from the foundational insights garnered from the integrative analysis of qualitative and computational findings detailed in the prior sections. This approach illuminates the pressing needs within the high-needs and ASD pediatric populations, guiding the development of a digital solution aimed at bridging critical care gaps. The “pediPASS” app emerges as a tool to address the unique challenges identified, with a focus on providing mental health resources, safety planning, and enhanced access to care.

The "pediPASS" app represents a transformative leap from traditional, paper-based safety planning to a dynamic, digital platform. Historically, safety plans have been static documents, rarely shared beyond the individual and their immediate mental health provider. This limitation often results in a fragmented understanding of the individual's needs across the broader care team. The "pediPASS" app reimagines this process, offering a shared, interactive tool that ensures continuity of care and fosters a collaborative care environment.

Methods

The mockup phase in the application development process serves as a first step, transitioning from conceptual design to a tangible, visual representation that stakeholders can interact with and evaluate. This phase, informed by an integrated analysis of qualitative and computational research findings, particularly focuses on the needs and challenges faced by high-needs and ASD pediatric populations, aiming to create a user-centered digital solution^{430,431}. Mockups are developed using visual design software such as Sketch, Adobe Photoshop, and Figma, offering a detailed view of the app's intended functionality, user interface, and interaction flow without delving into actual code or structural development^{432,433}. Prototype mock-ups are important in representing user interfaces, mapping out the user journey through multiple linked screens^{125,434,435}. The development of mockups follows a systematic process beginning with requirements gathering, where the needs of children with high-needs and their caregivers are identified, alongside the integration requirements with the EHR for seamless communication among care team members. This is followed by sketching and wireframing to lay out the app's basic structure and layout, and then creating interactive designs to visualize the overall aesthetic and core functionalities. This iterative process allows for early user testing and feedback collection, which is essential for refining the app's design and ensuring its usability and effectiveness.

Developing mockups offers multiple advantages, such as visualizing the product, validating concepts, identifying issues early, enhancing user experience, improving communication, accelerating development, and lowering costs. These advantages highlight the importance of mockups in visualizing the product,

gathering, and incorporating feedback to refine the concept, identifying potential issues early in the development process, and ultimately creating a product that meets user expectations and business objectives. The mockup stage makes sure the final product is not only visually appealing but also functional, user-friendly, and aligned with the specific needs of its intended users⁴³⁶⁻⁴³⁹. By prioritizing this phase, developers can avoid costly revisions later in the development cycle and move towards creating an app that resonates well with users and stakeholders alike.

Application Requirements

The mobile and desktop technological application is envisioned as a digital safety planning application tailored for both children and their caregivers. It features a user-friendly login interface that unlocks access to essential safety plan components, including the identification of warning signs, the development of internal coping strategies, and the creation of lists for people and professionals who can offer help during crises. Beyond these core elements, the app extends its functionality to provide an array of mental health resources, local service access information, and engaging educational content on coping strategies. A standout feature of “pediPASS” is its personalized self-care daily checklist, complete with reminders and notifications to ensure timely completion of tasks. This personalized aspect of the app is further enhanced with sections tailored to specific conditions, like ASD, offering resources and information catered to the unique needs of each condition.

An important feature of the “pediPASS” app is that it integrates into Electronic Health Records (EHR), enabling a seamless communication flow between the care team, patients, and caregivers. This interoperability ensures that healthcare providers can actively contribute to and update the safety plan, thereby closing the gap in access to care and facilitating a more cohesive and informed approach to patient support. By bridging the divide in care access and providing targeted mental health support, “pediPASS” represents a forward-thinking solution that leverages technology to enhance the wellbeing of high-needs children and their families. The app embodies the practical application of the BD-LHS framework and sets a new standard for digital health interventions aimed at supporting some of the most vulnerable populations

in our communities. **Table 8.3** presents an overview of the core components and features of "pediPASS," a digital platform designed to enhance the safety and mental health support for high-needs children and their families. It details the application's multifaceted approach, which includes digital safety planning, enhanced resources, and educational content, and EHR integration for improved care coordination. Through features such as warning signs identification, internal coping strategies, social and professional support networks, and safety measures for the environment, the platform facilitates real-time updates and access for children, caregivers, and care providers. Additionally, it enriches user experience with access to mental health information, a directory of local services, interactive educational content, and personalized care checklists. The integration with EHR systems underscores the platform's commitment to comprehensive care coordination, ensuring that all members of the interdisciplinary care team are aligned in the child's care strategy. This table encapsulates the app's holistic approach to supporting the mental health and well-being of children and their families, highlighting its important features and benefits.

The "pediPASS" app, supported by a detailed mockup that follows, outlines step towards more integrated care for high-needs and ASD populations. By leveraging technology to merge critical safety planning with expansive mental health resources and care coordination, "pediPASS" is poised to fill existing gaps in care and support, ensuring children and their caregivers have the tools and resources needed to navigate challenges effectively. This app addresses the integrated qualitative and computational findings and represents a practical application of the BD-LHS framework, setting a new standard for digital health interventions in supporting vulnerable populations.

Table 8.3: Overview of pediPASS Core Components and Features

Core Component	Description
Digital Safety Planning	pediPASS digitizes the traditional safety plan elements, allowing for real-time updates and access by children, caregivers, and the entire interdisciplinary care team.
Warning Signs Identification	Allows users to record and update signs of crisis onset, making these insights accessible to caregivers and care providers.
Internal Coping Strategies	Facilitates the listing of personal coping mechanisms, shareable with the care team for support and advice.
Social and Professional Support Networks	Enables the creation of contact lists for personal support and professional intervention, crucial during crises.
Safety Measures for the Environment	Provides guidance on creating a safer environment, crucial for preventing self-harm.
Enhanced Resources and Educational Content	Enriched with a multitude of resources aimed at supporting the mental health and well-being of high-needs
Access to Mental Health Information	Offers links to vetted resources for in-depth understanding and support strategies for various conditions.
Directory of Local Services and Providers	A curated list of local healthcare and support services enhances access to necessary care.
Interactive Educational Content	Includes videos and articles on coping strategies and emotional regulation skills for ongoing education and self-help.
Personalized Care and Self-Care Checklists	Tailored checklists with reminders promote routine self-care practices, essential for mental health maintenance.
EHR Integration for Care Coordination	Interoperability and adherence to standards, ensuring seamless communication and data exchange across diverse healthcare systems and platforms.
Integration with EHRs (e.g. SMART on FHIR)	Enables healthcare providers to contribute to and monitor the safety plan, ensuring all members of the care team are aligned on the child's care strategy.

Prototype Mock-Up

This section introduces the mockup for “pediPASS,” a digital safety planning application tailored specifically for children and their caregivers. Central to this application’s design is its integration with her systems, enabling healthcare providers to actively update and communicate vital information about their patients. This feature is instrumental in ensuring that all members of the care team have up-to-date access to the child’s safety plan, facilitating a more coordinated and effective approach to care.

There are several key components that distinguish "pediPASS" as an essential tool in the landscape of pediatric healthcare:

1. **Interactive Safety Planning:** The app digitalizes critical elements of traditional safety planning, making them interactive and accessible to children, caregivers, and healthcare providers. This dynamic format allows for immediate updates and access, ensuring the safety plan evolves with the child’s needs.
2. **Tailored Resources and Communication Channels:** Beyond safety planning, the app provides a wealth of tailored resources and direct communication channels. This ensures caregivers and children have access to the latest mental health resources, local services, and direct advice from their care team.
3. **Enhanced Accessibility and Continuity of Care:** By centralizing the safety plan and associated resources within a digital platform, “pediPASS” enhances the accessibility of critical information and ensures continuity of care across different healthcare settings and providers.
4. **Comprehensive Care Team Integration:** Through seamless EHR integration, “pediPASS” bridges the communication gap between caregivers and healthcare providers. This ensures a unified approach to the child’s safety and well-being, allowing for timely interventions and adjustments to the safety plan.

The development of the "pediPASS" is in response to the identified needs and challenges within the high-needs and ASD pediatric populations, as revealed through an integrated analysis of qualitative and computational research findings. This application is designed to address the immediate need for safety planning and contribute to the broader goal of improving healthcare outcomes and resources. The following table includes a breakdown of the app structure, key features, and functionality (**Table 8.4**). This mockup serves as a foundational guide and it can be further detailed and adjusted based on user feedback, specific requirements for accessibility, and the unique needs of children with various conditions.

The mockup for the "pediPASS" health app is designed with user experience at its core, featuring simple navigation bars strategically placed at the top or bottom to provide easy access to the main sections, including the dashboard, safety plan, resources, and personalized content. The dashboard organized into clearly segmented areas, facilitating quick access to crucial features of the app. To engage users and simplify the input process, interactive elements such as sliders, checkboxes, and dropdowns are integrated, specifically for contributing information to the safety plan. Furthermore, the interface is made child-friendly and easy to navigate using visual icons and color coding, distinguishing between different sections and features. This design ensures that the app is accessible and inviting to young users, encouraging interaction, and enhancing the overall user experience for children and their caregivers alike. **Figure 8.3** presents a mockup of the "pediPASS" app design in mobile format, illustrating a potential layout that includes a login page and various sections of the app such as the safety plan, contacts, resources, and information about healthcare services. This visual representation offers a glimpse into how the app could look, showcasing its user-friendly interface tailored to provide easy navigation and quick access to essential features for children and caregivers.

Table 8.4: Feature Overview of the 'pediPASS' Application Mockup

Feature	Description
Login/Registration Page	
For Caregivers and Patients	Separate login options for caregivers and patients to ensure tailored access and functionalities.
For Health Professionals	A secure login for health professionals to view and update patient safety plans, ensuring interoperability within health systems.
Dashboard/Home Page	
Overview	A welcoming dashboard that highlights the app's key features, including access to the safety plan, mental health resources, and personalized sections.
Quick Access Menu	Icons or buttons for 'Safety Plan', 'Resources', 'Local Services', and 'Profile Settings'.
Safety Plan	
Step-by-Step Guide	Interactive sections for creating and updating a safety plan, including identifying warning signs, developing coping strategies, supportive people and settings, personal and professional contacts for crises, and environmental safety tips.
Personalization	Ability to customize according to the patient's condition, e.g., ASD-specific strategies and supports.
Mental Health Resources	
Educational Content	Articles, videos, and guides on coping strategies, understanding mental health conditions, and promoting well-being.
Interactive Elements	Quizzes or self-assessment tools to engage children and caregivers in learning about mental health.
Accessing Local Services	
Search Functionality	A feature to find local mental health services, support groups, and emergency contacts based on the user's location.
Contact Information	Detailed listings with contact information, operating hours, and services offered by local agencies and professionals.
Personalized Sections for Individual Conditions	
Tailored Content	Sections specifically designed for various conditions, offering specialized resources, coping mechanisms, and support networks.
Customizable Interface	The ability for users to customize their experience based on the patient's needs and preferences.
Profile and Settings	
User Profiles	Separate profiles for caregivers and patients, allowing for personalized settings and access levels.
Privacy and Security Settings	Options to control the sharing of information with health professionals and caregivers.
Interoperability with Health Systems	
Care Team Access	Secure functionality for health professionals to access, add, or update safety plans and view patient progress.
Integration	Smooth integration with existing health records and systems for a holistic view of the patient's health journey.



Figure 8.3: Mockup of Pediatric Portal to Access Safety & Services (pediPASS) – (1-5) Login and sign-up views; (6) Home page with overview of safety plan and menu to accessing services/mental health resources; (7) Services page with specialists' information, local healthcare providers, and services; (8) Self-Care Checklist with calendar and list of personalized daily goals.

8.4 Implementation Strategy & Recommendations

Introduction

This section provides a general overview of the implementation strategy for the “pediPASS” app based on the mockup that was detailed in the preceding section. An implementation strategy refers to the overarching approach or set of actions designed to ensure that an intervention is adopted and executed effectively within an organization or system. The general implementation strategy is followed by an implementation blueprint. While an implementation strategy offers a broad framework for how to achieve change in practice, an implementation blueprint provides the detailed plan based on that strategy, outlining specific actions and resources needed for successful implementation. The strategy sets the direction and approach, while the blueprint lays out the plan for execution. The implementation strategy and blueprint can serve as a guide for integrating the digital safety planning tool into healthcare settings. The “pediPASS” app aims to bridge the gap in mental health support for children and their caregivers by offering a user-centered, secure, and interactive digital tool. By adhering to this implementation blueprint, the project can achieve its goal of enhancing mental health awareness, support, and intervention, leveraging technology to make a positive impact on the lives of children and their families.

Methods

Implementation strategies are important to strive towards efficient and successful development and deployment of interventions or technological solutions. The implementation strategy for the pediPASS app will consider the integrated findings that informed the app’s design, features, and integration with existing EHR systems. The strategy will address technical, ethical, and user-experience aspects, ensuring that the app is functional, accessible, secure, and responsive to the needs of high-needs children and their caregivers. The implementation blueprint outlines the key components and phases for developing and implementing the app to be used by patients and caregivers.

An implementation strategy provides a framework for the successful deployment of technologies in healthcare practices. This strategy, particularly for the "pediPASS" app, is informed by a synthesis of methodologies from implementation science, user-centered design, and health informatics. Each discipline contributes unique principles that collectively ensure the app's effective integration into clinical settings.

Implementation science frameworks such as the Consolidated Framework for Implementation Research (CFIR) and Expert Recommendations for Implementing Change (ERIC) aim to enhance intervention adoption and sustainability within healthcare settings. CFIR provides an outline of factors that may influence the implementation success, categorizing them into five domains: (1) intervention characteristics, (2) inner setting, (3) outer settings, (4) characteristics of individuals involved, and the (5) implementation process itself^{121,154}. These determinants can either facilitate or hinder the adoption of healthcare innovations. The ERIC study offers a set of actions to support the implementation process^{122,123}. These strategies range from infrastructural changes to developing stakeholder interrelationships and engaging patients. The CFIR-ERIC Matching Tool facilitates the selection of these strategies by linking them directly to identified CFIR barriers, thereby optimizing the implementation approach based on the specific challenges and needs within the healthcare setting^{124,440}. By inputting identified barriers into the tool, it generates a set of strategies tailored to address those specific challenges, thereby optimizing the implementation effort.

The CFIR-ERIC tool enables the "pediPASS" app development team to systematically identify and address potential barriers to implementation, ensuring a tailored approach that considers the complex dynamics of healthcare settings^{124,441}. This methodological approach aids in strategizing for successful app rollout and in refining the implementation process over time, thereby enhancing the app's adaptability and effectiveness in real-world contexts. Furthermore, the strategy emphasizes the importance of planning and executing the implementation process, guided by the insights gained from the CFIR and ERIC frameworks. It highlights the necessity of engaging healthcare providers and patients in the design and rollout phases, ensuring that the app is user-centered to addresses the specific needs and preferences of its intended users⁴⁴². The strategic integration of CFIR and ERIC into the "pediPASS" app's implementation strategy represents an approach

to overcoming the inherent challenges of introducing healthcare innovations. By systematically identifying barriers and matching them with expert-recommended strategies, the app is positioned for a successful adoption and sustained impact within healthcare settings.

Closely echoing goals of the implementation science frameworks, the principles of user-centered design ensure that the development of the app prioritizes the end-users' needs and experiences. Literature emphasizes the importance of involving users throughout the design and development process to foster the creation of digital tools that are both intuitive and accessible^{45,443–445}. For "pediPASS," this entails the active participation of children with high-needs, their caregivers, and healthcare providers in the design process, ensuring the app meets their specific requirements and significantly enhances the user experience. This approach is crucial for developing an app that is functional, user-friendly, and effective in meeting the unique needs of its intended audience.

Integrating the "pediPASS" app with existing EHR systems leverages health informatics principles, which are crucial for ensuring interoperability and secure patient data management. Health informatics is essential for the successful integration of digital tools into healthcare practices, enabling contextual data exchange and improving continuity of care⁴⁴⁶. This integration is made possible through the application of data standards, which facilitates the connection between healthcare applications and EHR systems in a secure and interoperable manner. SMART on FHIR (Substitutable Medical Applications, Reusable Technologies on Fast Healthcare Interoperability Resources) is a set of specifications that build on the FHIR standard to enable the development of interoperable healthcare applications^{447–449}. The integration of the "pediPASS" app with EHR systems through SMART on FHIR is essential to ensure that the app can efficiently access the patient safety plan within the EHR. This integration allows for seamless interaction, enabling patients to easily access their safety plans and healthcare providers to effortlessly update and manage these plans. The use of SMART on FHIR facilitates secure and standardized data exchange between the app and EHR systems, enhancing the overall usability and effectiveness of "pediPASS" in supporting patient care and safety.

ERIC Strategies

To enhance the implementation strategy for the "pediPASS" app, the CFIR-ERIC matching tool is used to align chosen ERIC strategies with identified CFIR constructs^{122,123,440}. CFIR constructs identified in the qualitative study (Chapter 3), such as Patient Needs and Resources, Adaptability, Available Resources, and Knowledge & Beliefs about the Intervention, guide the selection of ERIC strategies. **Table 8.5** details how each strategy is integrated into the development and deployment of the app, reflecting the qualitative insights from the dissertation's findings. This structured approach aims to ensure that pediPASS is a user-centric tool that successfully navigates the complexities of healthcare delivery for the ASD community.

Each of the CFIR constructs identified from the qualitative work is listed as a column of the table and the matching tool indicates the percentage of importance. The top ERIC strategies are identified, and strategies that have a cumulative percentage of greater than 50% are included for consideration in tailoring the implementation strategy. For *Patient Needs and Resources*, strategies may include developing educational materials and personal health planning tools within the app. *Adaptability* could be addressed by incorporating features that allow customization of the app to fit individual patient needs. Ensuring *Available Resources* might involve securing funding for sustained app support and updates, while strategies to enhance *Knowledge & Beliefs about the Intervention* could involve engaging with caregivers and patients through workshops and feedback sessions to foster trust and awareness about the app's benefits. By leveraging these ERIC strategies, the "pediPASS" app can be tailored to overcome barriers and meet the complex needs within healthcare settings, promoting a seamless integration into clinical practice and the daily lives of patients and caregivers.

Table 8.5: CFIR-ERIC Matching Tool^{122,123,440} – Implementation Strategies Tailored for pediPASS Deployment

ERIC Strategies	Total %	Adaptability	Patient Needs & Resources	Available Resources	Knowledge & Beliefs about the Intervention	Strategy for pediPASS
Conduct local needs assessment	116%	35%	57%	0%	24%	Engage with local ASD communities to ensure pediPASS meets the specific needs of users in Rhode Island.
Promote adaptability	108%	73%	14%	4%	16%	Design pediPASS to be customizable to support individual user preferences and care requirements.
Assess for readiness and identify barriers and facilitators	97%	31%	33%	13%	20%	Evaluate the healthcare landscape to identify how pediPASS can integrate smoothly with existing EHR systems and patient care workflows.
Capture and share local knowledge	90%	35%	10%	22%	24%	Use pediPASS as a platform for caregivers and healthcare providers to exchange knowledge and best practices.
Access new funding	86%	0%	0%	78%	8%	Seek grants and partnerships to ensure the sustainable development and maintenance of pediPASS.
Obtain and use patients/consumers and family feedback	84%	4%	76%	0%	4%	Implement a feedback mechanism within pediPASS to collect user input for continuous improvement.
Involve patients/consumers and family members	79%	8%	71%	0%	0%	Actively involve ASD patients and their families in the design and testing phases of pediPASS.
Conduct educational meetings	77%	12%	10%	0%	56%	Host workshops to educate stakeholders about the features and benefits of pediPASS to promote its adoption.
Identify and prepare champions	72%	23%	5%	4%	40%	Recruit influential individuals such as healthcare providers and organizational leaders within the ASD community who can advocate for the app's use and encourage engagement.
Conduct local consensus discussions	71%	31%	29%	0%	12%	Facilitate discussions with local health practitioners and caregivers to ensure pediPASS aligns with community needs and values.
Tailor strategies	70%	35%	14%	9%	12%	Customize pediPASS's deployment strategies to fit the specific contexts of various healthcare settings within Rhode Island.
Build a coalition	63%	15%	14%	17%	16%	Form partnerships with ASD advocacy groups, healthcare providers, and tech developers to support the widespread implementation of pediPASS.
Develop educational materials	61%	12%	10%	4%	36%	Create user guides and informational content to help users navigate and maximize the app's mental health resources.
Conduct cyclical small tests of change	58%	23%	10%	13%	12%	Implement iterative testing phases for pediPASS, using feedback to make incremental improvements to the app's functionality.
Facilitation	51%	27%	0%	4%	20%	Establish a dedicated support team to assist users with any technical or operational issues, ensuring a smooth experience with pediPASS.

Implementation Strategy

The implementation strategy for the "pediPASS" app is a multidisciplinary endeavor that leverages the strengths of implementation science, user-centered design, and health informatics. This approach ensures that the app is effectively integrated into healthcare settings, addressing the critical needs of children with high-needs and their caregivers. The general implementation strategy for the "pediPASS" app involves a collaborative effort with Lifespan Pediatric Behavioral Health Emergency Services, local community organizations such as the Rhode Island Parent Information Network (RIPIN), and other mental health facilities and departments within Rhode Island's healthcare network. This strategy emphasizes partnering with healthcare providers and caregivers from the outset to gather feedback on the app's prototype and subsequent iterations of the live application. Such collaboration is crucial for refining the app's features and functionalities, ensuring they effectively address the users' needs and seamlessly integrate into healthcare providers' workflows. Feedback loops, facilitated through focus groups and pilot testing phases, will inform continuous improvements, enhancing user satisfaction and engagement.

This strategy adopts a phased, iterative approach designed to ensure the app's effective integration into Rhode Island's pediatric mental health ecosystem. The strategy begins with pre-implementation activities, focusing on building partnerships with key stakeholders, including healthcare providers, caregivers, and IT specialists from hospital network, among others. This initial phase is crucial for establishing buy-in and understanding the specific needs and gaps in mental health support and safety planning that the app aims to address. A thorough assessment of the technical infrastructure within healthcare facilities is also undertaken to ensure system compatibility and identify any necessary technological adjustments. Following this foundational work, the strategy progresses to prototype feedback and iteration. Here, the app's prototype is shared with stakeholders to elicit feedback on its design, usability, and functionality. This feedback informs iterative design updates, enhancing the app's user experience and operational efficacy. A pilot testing phase allows for real-world evaluation of the app, providing valuable insights into its impact and areas for improvement. The full implementation and training phase marks the official launch of the

"pediPASS" app across targeted facilities and departments. Training sessions ensure that both healthcare providers and caregivers are well-equipped to use the app effectively. Additionally, ongoing support systems are established to resolve any technical issues swiftly, maintaining high user satisfaction. The final phase centers on evaluation and continuous improvement. Continuous monitoring of the app's usage and effectiveness facilitates the collection of data on its impact on patient care. Structured feedback mechanisms enable the gathering of insights from users and stakeholders, which are critical for guiding future updates and enhancements. Lastly, the scalability of the app is assessed, with an eye towards broader adoption across additional regions or healthcare systems. Overall, this implementation strategy ensures a systematic and responsive rollout of the "pediPASS" app, aiming to significantly enhance mental health support and safety planning for children with high-needs and their families. By adhering to this structured approach, the strategy seeks to improve healthcare outcomes and support the well-being of this vulnerable population within Rhode Island and potentially beyond.

Below is an outline for an implementation blueprint. It outlines the step-by-step processes, general timelines, and key milestones for the deployment of the "pediPASS" app, detailing the collaborative efforts with stakeholders across Rhode Island's healthcare ecosystem. This strategy identifies ways the "pediPASS" app will be operationalized to provide better care and support for children with high-needs and their families, ensuring a cohesive and well-coordinated approach to mental health services.

Implementation Blueprint

The implementation blueprint for the "pediPASS" app outlines an adaptive strategy for introducing a mental health management tool into healthcare practices. By combining rigorous requirement analysis, user-centered design principles, and a strong emphasis on privacy and security, the blueprint provides a strategy for successful implementation and uptake. **Table 8.6** provides a structured overview of the essential components in the pediPASS implementation blueprint, outlining the project's goals and objectives, scope and boundaries, stakeholders and their roles, strategies and actions including a five-phase implementation strategy, timeline, resources required, and considerations for security, privacy, evaluation, training,

communication, sustainability, and user-centered design. This framework is designed to guide the development, deployment, and continuous improvement of the pediPASS application, ensuring it meets the needs of patients, families, and healthcare providers while adhering to high standards of data protection and user engagement.

Transitioning from this overview, **Figure 8.4** illustrates a high-level roadmap of the pediPASS project, encapsulating a five-phased approach that progresses from pre-implementation through to sustainability. The process begins with Phase 1, where the groundwork is laid out by defining app requirements and ensuring compliance with healthcare standards. The project moves into Phase 2, focusing on the technical development of the app, including critical security measures. Phase 3 shifts the focus to rigorous prototype testing, collecting feedback from users to refine the app. Phase 4 marks the transition from theory to practice, where the app is integrated into healthcare settings and goes live. The final Phase 5 shifts towards long-term goals, monitoring the app's performance and iterating improvements to enhance its value and effectiveness. This phased strategy ensures a methodical rollout with continuous refinement, aiming for a user-centric platform that evolves with the needs of its stakeholders. **Table 8.7** describes the specifics of each phase within the implementation blueprint. This detailed breakdown details the objectives, key activities, and expected outcomes for each stage of the project, from initial planning and design through to development, testing, deployment, and ongoing evaluation. This phase-specific overview aims to provide clarity on the project's progression, timelines, and dependencies, ensuring a coherent and strategic approach to the successful implementation of pediPASS.

Table 8.6: Overview of Key Components in the pediPASS Implementation Blueprint

Overview of Implementation Blueprint Components		
Category	Sub-Category	Details
Goals and Objectives	Real-time Access	Provide real-time access to personalized safety plans and mental health resources for patients and families.
	Healthcare Provider Support	Enable healthcare providers to seamlessly add and update safety plan information within the EHR system.
	Patient Engagement	Promote patient engagement with daily self-care practices and facilitate access to mental health support services.
Scope and Boundaries	Data Privacy and Security	Ensure data privacy and security in full compliance with HIPAA standards.
	App Development	The project encompasses the development of both mobile and desktop versions of the app, with integration into EHRs via SMART on FHIR.
Stakeholders and Roles	Clinical Complement	It is designed to complement, not replace, traditional clinical consultations, enriching the existing mental health care framework.
	Project Manager	Leads project execution, adhering to timelines and quality benchmarks.
	Healthcare Providers IT and Development Team	Input on safety plan design/content, app functionality feedback. Manages app development, FHIR integration, and data security.
Strategies and Actions	Patients and Families	Provide user experience feedback during testing.
	Compliance Officer	Confirms adherence to HIPAA and other privacy regulations.
	Planning and Design	Phase 1: Gather needs assessments, define app features, and establish privacy/security protocols.
	Development	Phase 2: Use Agile methodology for app development, ensure EHR compatibility via SMART on FHIR, and implement data protection measures.
Timeline	Prototype Testing	Phase 3: Beta testing with stakeholders, application refinement, and development/delivery of training materials.
	Integration and Deployment	Phase 4: Clinical setting deployment, performance monitoring, and iterative improvements based on feedback.
	Evaluation and Improvement	Phase 5: Continuously assess app's impact and user satisfaction, using feedback to guide agile development cycles for enhancements.
Resources Required	Duration of Phases	The amount of time for each phase will vary and depend on organization capabilities, resources, and other factors
	Development and Compliance Training and Support	Development tools, platforms, and expertise in SMART on FHIR and HIPAA compliance. Training materials, support infrastructure, and marketing/communication tools.
Security Considerations	Encryption and Integration	Implement encryption and secure authentication to safeguard data collaboration with EHR vendors for integration with SMART on FHIR
Privacy Considerations	HIPAA Adherence	Adherence to HIPAA regulations through encryption, role-based access control, and periodic audits.
Evaluation and Metrics	User Engagement and Compliance	Monitor user engagement, collect feedback, and conduct compliance audits for HIPAA adherence.
Training and Support	Resources and Training	Provide online resources and detailed training for healthcare providers, supported by technical support.
Communication Plan	Engagement and Marketing	Engage healthcare providers with announcements and demos and inform patients/families about app features.
Sustainability and Scalability	Updates and Expansion	Regular updates for EHR compatibility, plans for user base expansion, and continuous evaluation for enhancements.
User-Centered Design	Continuous Improvement	Maintain dialogue with users and employ a flexible, iterative design and testing approach for ongoing app evolution.

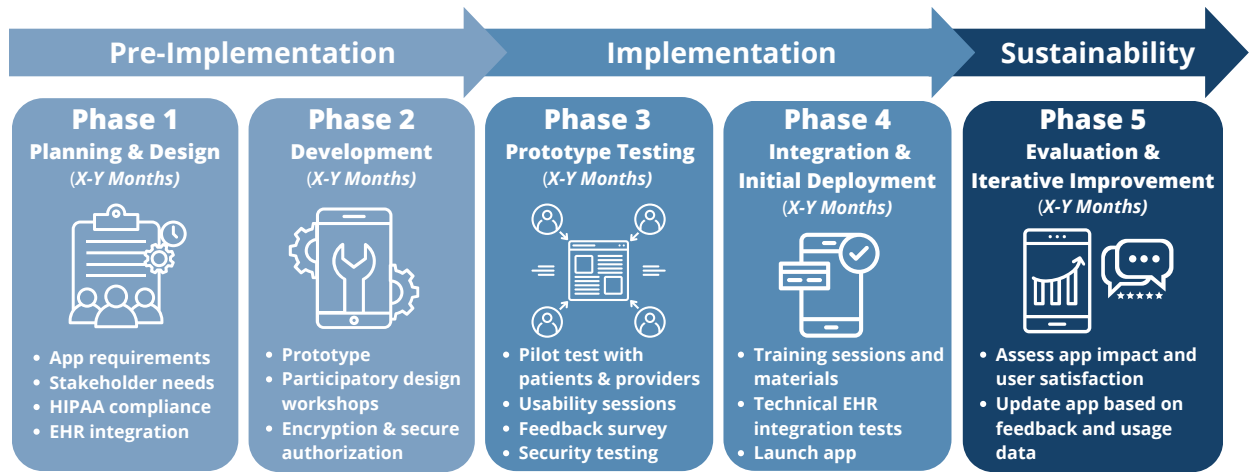


Figure 8.4: Roadmap for pediPASS Five-Phase Implementation Blueprint

Table 8.7: Detailed Breakdown of the Five-Phase Implementation Blueprint for pediPASS

Phase	Duration	Description	User-Centered Design	Key Activities
1 Planning & Design	X-Y months	Initial phase focused on gathering requirements, defining app features, and establishing security protocols.	User research to understand needs and preferences, plan for accessibility and inclusivity	Stakeholder engagement, market analysis, resource allocation, technical and Architecture planning, HIPAA compliance, SMART on FHIR API
2 Development	X-Y months	Agile development of the app, ensuring compatibility with EHR systems and incorporating data protection measures.	Developing based on iterative feedback, accessible and inclusive design	Core feature development, availability of development tools and platforms, participatory design workshops
3 Prototype Testing	X-Y months	Testing the app with stakeholders to refine its functionality and develop training materials.	Engaging users in testing and feedback, adjustments based on user feedback	Pilot testing, usability testing, stakeholder participation and feedback, data security testing
4 Integration & Initial Deployment	X-Y months	Prepare for and execute the launch of the app, ensuring it integrates well with existing healthcare infrastructures and is accessible to all target users.	Final user validation to ensure needs are met, provide guides and training for ease of use	Full system integration, technical integration tests with EHR systems, documentation, training sessions and materials
5 Evaluation & Iterative Improvement	Continuous	Continuously monitor, evaluate, and update the app based on user feedback and performance metrics to enhance its effectiveness and user experience.	Ongoing collection of user feedback, monitor user engagement and experience for improvements	Continuous user feedback, performance evaluation, iterative updates, technological advancements, regulatory changes

8.5 Conclusion

In conclusion, this work illustrates the potential integration phase of the BD-LHS framework through the synthesis of qualitative insights from caregivers of children with high-needs with computational analyses from statewide health data. This approach has led to the conceptualization and proposal of the "pediPASS" application, a technological intervention designed to enhance the mental health and safety of high-needs children and their caregivers. By merging the strengths of qualitative and quantitative research, this aims to address gaps in healthcare provision, presenting an evidence-based solution deeply informed by the experiences and needs of its target users.

The development of pediPASS exemplifies the potential of interdisciplinary research within the LHS paradigm, showcasing a method for future healthcare innovations. It highlights the role of integrating diverse research methodologies to gain an understanding of healthcare challenges, thereby improving the development, implementation, and efficacy of interventions. The proposed implementation strategy for pediPASS provides an approach for navigating the complexities of integrating technology into healthcare settings, focusing on user engagement, data privacy, and system compatibility. Incorporating ERIC strategies, the pediPASS app and implementation process is set up to overcome barriers and meet the complex needs within healthcare settings. This approach promotes seamless integration into clinical practice and the daily lives of patients and caregivers, ensuring that the app effectively addresses specific challenges in the ASD community.

Aim 3 affirms the foundational principle of the BD-LHS framework: the synergy of qualitative insights with computational analytics can lead to significant improvements in healthcare outcomes. As the research moves towards implementing and evaluating pediPASS, it contributes to the continuous learning and improvement of healthcare delivery. Overall, this aim sought to meet the identified needs of these children and their caregivers, and potentially establish a precedent for the application of the BD-LHS framework in broader healthcare intervention development. The goal is to design and deploy healthcare solutions that are cyclically refined through integrated knowledge discovery and implementation strategies.

Chapter 9: Conclusion

List of Chapter Acronyms

ADHD = Attention-Deficit/Hyperactivity Disorder
ASD = Autism Spectrum Disorder
BD-LHS = Bridge to Discovery in Learning Health Systems
EHR = Electronic Health Record
HIE = Health Information Exchange
LHS = Learning Health System
NLP = Natural Language Processing

Preface

This section transitions to the final reflections, summarizing the dissertation's key insights and contributions. It offers a recap of the different ways this work studied and addressed the complexities faced by children with high-needs, especially those with Autism Spectrum Disorder (ASD). This was done through a convergent mixed methods approach by the application of the Bridge to Discovery in Learning Health Systems (BD-LHS) nested framework. The dissertation provided a scoping review of health informatics, and detailed qualitative and quantitative analyses to identify and address gaps in care. The findings were synthesized to further enhance knowledge discovery with the goal of informing the concept and design of the "pediPASS" app, a user-centered digital solution aimed at enhancing mental health support and care coordination. This chapter concludes by acknowledging the limitations and provides suggestions for future research, ensuring continued progress in understanding, and addressing the needs of high-needs children, particularly those with ASD to contribute to the iterative LHS and improve care for these individuals.

9.1 Summary

This dissertation, framed within the LHS framework, undertook an investigation into the complexities facing children with high-needs, particularly those with ASD. Using a convergent mixed methods approach, it combines qualitative insights from caregivers with computational analyses to provide a layered

understanding of the issues these families face. This methodology enriches the data landscape and highlights the synergy between evidence-based practice and real-world data, fostering an ongoing cycle of care improvement.

Through the BD-LHS framework, this research gathered and synthesized perspectives from varied data sources. The integration of qualitative and quantitative findings enhances the findings, where in-depth qualitative insights from focus groups add richness and context, capturing the important experiences of patients and their families. Simultaneously, quantitative analyses of clinical data uncover patterns and trends that are essential for discovery and informed strategic planning, offering a broad-scale perspective on prevalence, risk factors, and outcomes. The synergy between these two types of findings significantly enhances the development and refinement of interventions. It ensures that the interventions are grounded in empirical evidence and informed by the real-world experiences and needs of the community. This holistic understanding enables the creation of more targeted and effective interventions that can address both the broad patterns identified through quantitative analysis and the specific, individualized needs highlighted by qualitative research.

Chapter 1 introduced the conceptual underpinnings of the LHS and set the stage for a detailed investigation into how data-driven insights could inform more effective and personalized care strategies for high-needs populations. Chapter 2 provided a scoping review of health informatics methods and their application in understanding and addressing the complexities associated with ASD. This chapter also illuminated significant gaps in existing work, specifically highlighting the need for enhanced information sharing, patient education and engagement, and focused efforts to decrease health disparities for patients with ASD. These gaps emphasize the importance of leveraging clinical data to optimize patient care and support systematic research efforts, thereby enriching our understanding of ASD and improving treatment strategies.

Chapter 3 (Aim 1) delved into the experiences of caregivers of high-needs children through qualitative focus groups and thematic analysis. Caregivers voiced significant challenges related to accessing

specialized care, managing mental health issues, and coping with the social isolation their children face. These insights lay the groundwork for understanding current care system gaps and the urgent need for additional resources and interventions.

Chapter 4 (Aim 2(a)) characterized the high-needs pediatric population using HIE data, shedding light on comorbidities, care needs, and healthcare utilization patterns. Chapters 5-7 (Aim 2(b-d)) shifted the focus to computational methods, examining the ASD population and associated comorbidities through statewide clinical data including medical claims, electronic health record (EHR) ED notes, and Health Information Exchange (HIE). These computational analyses identified patterns in mental health comorbidities using unsupervised learning, described profiles of different ASD groups through clustering techniques, and identify risk factors for suicidal thoughts and behaviors through use of predictive modeling. This quantitative exploration highlighted the need for targeted mental health interventions.

Chapter 8 (Aim 3) integrated the qualitative and computational findings, offering a view of the challenges and needs of high-needs children. The integration of qualitative and quantitative findings in this aim illuminated the complex challenges encountered by high-needs children and their families. The qualitative data revealed detailed caregiver narratives about the difficulties in managing mental health issues and navigating healthcare services, while the quantitative analysis confirmed the high prevalence of mental health comorbidities like anxiety, depression, and ADHD among children with ASD. This congruence between the lived experiences of caregivers and the statistical data accentuated the critical need for accessible mental health services and enhanced healthcare navigation support for ASD patients and the broader high-needs pediatric population. The study's structured approach facilitated an understanding of these issues, laying the groundwork for targeted interventions and systemic improvements in care.

This led to the conceptualization of a technology-based application designed to address the identified challenges. The app, informed by both caregiver narratives and clinical data, represents a tangible solution aimed at enhancing mental health support, facilitating access to specialized care, and ensuring continuity of care through improved communication with healthcare providers. By addressing the gaps in information

sharing, patient education, and engagement, and targeting health disparities, the pediPASS app mockup served as a direct response to the critical areas of need. The app is designed to offer a suite of features, including safety planning for suicidal thoughts and behaviors, personalized self-care checklists, and a wealth of mental health resources, educational materials, and videos. It also sought to facilitate easier access to services, therapies, support groups, and more, acknowledging the difficulties many families face in navigating the healthcare system. The app's integration with EHR stands to enhance communication between families, healthcare providers, and interdisciplinary teams, fostering greater continuity of care—a critical need highlighted by the integrated findings from both the qualitative and quantitative analyses. These features are informed directly by the synthesis of insights gathered from caregivers' experiences and computational data analyses, highlighting prevalent mental health comorbidities, the impact of social isolation, and systemic barriers to care access and utilization. By addressing these identified needs, the app concept represents a proactive step towards developing tailored, effective solutions for improving the well-being and healthcare experiences of high-needs children and their families.

The work culminates with an implementation strategy for the "pediPASS" app. This strategy, rooted in a collaborative and multidisciplinary approach, incorporates insights from implementation science, user-centered design, and health informatics to ensure the app's practicality and effectiveness. Through partnerships with healthcare providers and caregivers, the plan focuses on iterative feedback and refinement of the app. It unfolds across several phases, including stakeholder engagement, prototype testing, user training, and ongoing evaluation, with the goal of improving mental health outcomes and care coordination for this vulnerable group. These recommendations and strategies offer the potential to revolutionize mental health support for children with high-needs and their families. By navigating the complexities of healthcare provision with a user-centered digital solution, this work addresses specific gaps in care and sets a precedent for future innovations in pediatric mental health services. The collaborative efforts, rigorous methodological approach, and strategic deployment outlined underscore the commitment to enhancing

healthcare outcomes, marking a step forward in the integration of technology and care in addressing the needs of vulnerable populations.

9.2 Limitations

This dissertation contributes valuable insights into the care and needs of high-needs children, including those with ASD, however, it is important to acknowledge its limitations. The reliance on existing EHR data, HIE data, and medical claims presents the first set of limitations. These data sources, while rich and informative, might not fully capture the spectrum of unmet needs or healthcare experiences, particularly the interactions not formally documented within healthcare settings. This gap might leave out critical aspects of patient and caregiver experiences that could inform more personalized care strategies.

The limitations of medical claims data are notably significant, as this information is primarily designed for billing purposes rather than clinical insights. Consequently, the richness of clinical detail is often lacking, and the data might not accurately reflect the complexity of patient conditions and their care pathways. Similarly, HIE data, while facilitating a broader view of a patient's healthcare interactions across different providers, might not always be consistently detailed or complete. Variability in data entry practices and the scope of information shared across institutions can lead to inconsistencies in the comprehensiveness of the data available for analysis. EHR data, despite being a more direct source of clinical information, also has its limitations. These records can vary significantly in terms of detail, accuracy, and format, depending on the healthcare provider's practices and the specific EHR systems in use. Moreover, EHRs may not uniformly capture patient-reported outcomes or the subtleties of patient and family experiences with the healthcare system, which are crucial for understanding the full context of care needs.

Furthermore, quantitative analyses are subject to the limitations inherent in retrospective data. These limitations include potential biases and inaccuracies in diagnostic coding, which can affect the reliability of the findings derived from such analyses. Although statewide data offers significant benefits and Rhode Island's diverse population may serve as a representative microcosm of the nation's demographics, there are still limitations to drawing conclusions based solely on data from one state. Such an approach may not fully

account for regional variations in healthcare practices, policies, and access, which can influence care outcomes and needs.

Lastly, the qualitative component of this study, rich in caregiver narratives, provides invaluable insights into the lived experiences of families managing high-needs conditions. However, it may not fully represent the diversity of experiences across different geographic, socio-economic, and cultural contexts. The perspectives captured may predominantly reflect the experiences of those within specific communities or those who are more engaged with the healthcare system, potentially overlooking the voices and experiences of underrepresented groups. In summary, while this dissertation makes a significant contribution to the field, these limitations highlight the need for cautious interpretation of the findings and suggest areas for further research to enhance understanding of ASD care.

9.3 Future Directions

Addressing the limitations identified in this dissertation opens a pathway to several promising future research directions, each aimed at enhancing our understanding and care of high-needs children, including those with ASD. These directions are designed to validate and extend the findings of this work and operationalize these insights in a way that can improve patient care and healthcare practices. The initiative to extend data analysis beyond the confines of existing datasets to a national level stand as an important step forward. By expanding to national or external datasets, future studies can provide a more holistic view of the vast landscape of healthcare practices, access, and outcomes across the United States, thereby validating and enriching the insights from this study. Such an approach is crucial for tailoring care strategies to diverse regional healthcare ecosystems and identifying best practices for nationwide implementation.

In addressing the qualitative aspect of this study, it is imperative to broaden the spectrum of caregiver participation. Future research endeavors should strive to capture the rich tapestry of caregiver experiences by engaging a more diverse cohort that spans various socio-economic, geographic, and cultural milieus. This can be achieved through recruitment strategies that leverage technology, community partnerships, and

healthcare networks to ensure a representative sample. By capturing a wider array of narratives, researchers can uncover previously unexplored challenges and needs, thereby informing the development of more inclusive and responsive care interventions.

The potential of Natural Language Processing (NLP) to mine clinical notes, particularly from ED visits, represents a frontier for extracting nuanced insights into the crisis experiences of individuals with ASD. This approach promises to reveal the immediate precipitants of crises, the effectiveness of interventions deployed in emergency settings, and potential gaps in emergency care protocols. Such granular analysis is instrumental in crafting targeted emergency care guidelines and training programs for healthcare professionals, ensuring that individuals with ASD receive timely and appropriate care during crises. Advancing predictive modeling for suicidal thoughts and behaviors in ASD populations is another critical research avenue. Future models should aim for greater sophistication, incorporating a diverse array of predictive factors to enhance early detection and intervention. External validation of these models across different populations and settings will ensure their reliability and applicability in clinical practice. The integration of such models into routine healthcare screenings can revolutionize care management for individuals with ASD, allowing for timely preventative measures and personalized care planning.

Moreover, the exploration of clustering techniques to identify undiagnosed individuals with ASD opens new pathways for diagnostic refinement and a deeper understanding of the ASD spectrum. This approach can facilitate the early identification of ASD, ensuring timely intervention and support. Additionally, it can contribute to the ongoing effort to delineate the boundaries of the ASD spectrum, supporting the development of tailored therapeutic interventions that address the specific needs of newly identified subgroups.

The most critical and expansive direction for future research lies in the continued development and enhancement of an app like the pediPASS application proposed in this work. This process demands an inclusive, participatory design approach that engages patients, caregivers, and healthcare providers at every stage. By forging partnerships with local health institutions for the app's development and deployment in

Rhode Island, the project sets the stage for a scalable model that can be adapted and implemented in other regions. The iterative design process with iterative user testing and feedback, ensures that the pediPASS app evolves into a critical healthcare tool that addresses the unique needs of high-needs populations, particularly those with ASD. This collaborative, stakeholder-driven approach ensures the application meets the identified needs and sets new standards for technology in healthcare, ultimately driving continuous improvement in healthcare delivery and outcomes for high-needs populations.

In conclusion, these future research directions emphasize a commitment to advancing the field of health informatics and ASD care. By building on the insights and limitations of the current study, future work can potentially impact the healthcare experiences of high-needs children and their families, driving forward the principles of continuous improvement and evidence-based care within LHS.

9.4 Broader Implications

This work could significantly enhance support for children ASD and other high-needs groups by using the BD-LHS framework. This nested framework within the broader LHS paradigm emphasizes the use of mixed methods approaches for knowledge discovery to inform evidence-based interventions. By leveraging qualitative insights, computational findings, and the development of technological interventions, the BD-LHS framework represents an integrated approach to healthcare knowledge discovery. The work presented in this dissertation bridges gaps to gain more holistic understanding of the ASD population. It advances ASD care by offering insights and practical solutions for improving the well-being and healthcare experiences of high-needs children and their families. By informing the development of a technology-based application tailored to the individual needs, this work contributes to a more adaptive and responsive healthcare system. This dissertation is an example of how a convergent mixed methods approach can bridge research and practice, contributing to the LHS's goal of perpetual care enhancement.

The research presented provides actionable insights for developing targeted interventions to address the gaps identified in each study and analysis. The "pediPASS" app showcases how to bridge these gaps,

offering a practical tool for families and caregivers by addressing adverse outcomes found in the data and tie in caregiver perspectives on the challenges they face in everyday life. It highlights the potential of technology to facilitate better healthcare navigation and support, underscoring the importance of a holistic approach to care. In moving forward, the integration of our findings into broader healthcare practices demands a continued commitment to innovation, collaboration, and advocacy. This entails the refinement of existing interventions like the "pediPASS" app and the exploration of new methodologies and technologies that can further support the unmet needs of these individuals. Central to this discussion is the critical need for improved mental health resources, better access to specialized services, and support for the overall well-being of high-needs children, including their emotional and social needs.

The implications of this work extend beyond ASD to inform broader healthcare practices. By emphasizing personalized care, the findings advocate for a healthcare system more attuned to the unique needs of and population or disease of interest. This approach enhances care delivery and supports the overall well-being of these vulnerable populations. The integration of research findings into practice demands collaboration among healthcare professionals, policymakers, and technology developers. It calls for a continued focus on innovation and advocacy to transform healthcare practices, ensuring all people, regardless of their needs, receive the comprehensive support necessary to thrive.

Appendix A

Data Extraction Table

	Year	Author	Title & Reference	Country	Informatics Subfield(s)	Informatics Method(s)	Research Objective(s)
1	2023	Raj	Analysis and Detection of Autism Spectrum Disorder Using Machine Learning Techniques ²⁰⁵	India	Clinical informatics	Machine learning, Convolutional Neural Networks (CNN), Support Vector Machine (SVM), Logistic Regression, K-Nearest Neighbors (KNN), Naïve Bayes	Discover New Knowledge; Case Identification/Database Infrastructure
2	2023	Fountain	Developmental Trajectories of Autism ¹⁸⁰	USA	Clinical informatics	Longitudinal study, group-based latent trajectory modeling	Discover New Knowledge
3	2023	Wallis	Prevalence of autism spectrum disorder in a large pediatric primary care network ¹⁸¹	USA	Clinical informatics	Retrospective cohort study, electronic health record (EHR) analysis	Discover New Knowledge
4	2023	Hightshoe	Barriers to Referral and Evaluation and Corresponding Navigation Services for Toddlers Screening Positive for Autism Spectrum Disorder ²²⁶	USA	Clinical informatics	Qualitative analysis, patient navigation	Reduce Health Disparities
5	2023	Heyl	Data quality and autism: Issues and potential impacts ²¹⁴	UK	Clinical informatics	Retrospective analysis, random forest classifiers, regression modeling	Discover New Knowledge
6	2023	McDonald	Predicting Autism from Head Movement Patterns during Naturalistic Social Interactions ²⁴³	USA	Clinical Research Informatics	Machine learning, computer vision	Discover New Knowledge
7	2023	MacFarlane	Consistency and reliability of automated language measures across expressive language samples in autism ²⁴⁴	USA	Clinical Research Informatics	Natural Language Processing, expressive language analysis	Discover New Knowledge
8	2023	Franco	Computer-aided autism diagnosis using visual attention models and eye-tracking: replication and improvement proposal ²⁴⁵	Brazil	Clinical Research Informatics	Eye-tracking, Visual Attention Models (VAMs), Neural Networks, Support Vector Machines, Random Forest	Discover New Knowledge; Early Detection: Diagnostics/Screening Tool
9	2023	Crowell	A Mixed Reality Full-Body Interactive Experience to Encourage Social Initiation for Autism: Comparison with a Control Non-digital Intervention ²⁵⁹	Not specified	Consumer health informatics	Mixed reality (MR) experiences, full-body interaction, video coding, physiological data analysis (HRV & EDA), anxiety questionnaire	Intervention/Therapy Development
10	2023	Oakley	Molehill Mountain feasibility study: Protocol for a non-randomised pilot trial of a novel app-based anxiety intervention for autistic people ²⁵⁴	UK	Consumer Health Informatics	Non-randomised pilot trial, app-based intervention	Intervention/Therapy Development
11	2023	Mazumdar	Mobile application-based early educational intervention for children with autism – a pilot trial ²⁵⁵	India	Consumer health informatics	Mobile application, early educational intervention	Intervention/Therapy Development
12	2023	Gholipour	Perceptions of the Professionals and Parents of Children with Autism Spectrum Disorders About Autism Services; A Qualitative Study ²⁸⁹	Iran	Public health informatics	Qualitative study, content analysis	Reduce Health Disparities
13	2023	Sia	Parent coaching via telerehabilitation for young children with autism spectrum disorder (ASD): Study protocol for a randomised controlled trial ³⁰³	Singapore	Telehealth	Randomised controlled trial, telerehabilitation, video conferencing	Intervention/Therapy Development; Patient Education/Patient Engagement

14	2023	Marino	TeleRehabilitation of Social-Pragmatic Skills in Children with Autism Spectrum Disorder: A Principal Component Analysis ²³²	Italy	Telehealth; Clinical Research Informatics	Principal Component Analysis (PCA), telehealth intervention	Intervention/Therapy Development
15	2023	Johnson	Telehealth parent training for sleep disturbances in young children with autism spectrum disorder: A randomized controlled trial ²³³	USA	Telehealth; Clinical Research Informatics	Randomized controlled trial (RCT), telehealth delivery	Intervention/Therapy Development
16	2023	Su	Telehealth Versus Face-to-Face Fine Motor and Social Communication Interventions for Children With Autism Spectrum Disorder: Efficacy, Fidelity, Acceptability, and Feasibility ²³⁸	USA	Telehealth; Clinical Research Informatics	Randomized controlled trial, videoconferencing	Intervention/Therapy Development; Discover New Knowledge
17	2022	Gutierrez-Sacristán	Multi-PheWAS intersection approach to identify sex differences across comorbidities in 59,140 pediatric patients with autism spectrum disorder ¹⁷⁸	USA, Spain, Netherlands	Clinical informatics	Phenome-Wide Association Studies (PheWAS), intersection approach	Discover New Knowledge
18	2022	Ahmed	Toward Machine Learning-Based Psychological Assessment of Autism Spectrum Disorders in School and Community ¹⁷⁹	Bangladesh, UK	Clinical Informatics	Machine learning, artificial neural network, questionnaire-based assessment	Discover New Knowledge
19	2022	Masum	A Comparative Study of Machine Learning-based Autism Spectrum Disorder Detection with Feature Importance Analysis ²⁰⁴	USA, Bangladesh	Clinical informatics	Machine learning, neural network, feature importance analysis	Discover New Knowledge; Early Detection: Diagnostics/Screening Tool
20	2022	Schuchard	Using percentiles in the interpretation of Patient-Reported Outcomes Measurement Information System scores: Guidelines for autism ¹⁹⁹	USA	Clinical informatics	Patient-Reported Outcomes Measurement Information System (PROMIS), statistical analysis	Discover New Knowledge
21	2022	Fombonne	Validation of Autism Diagnosis and Clinical Data in the SPARK Cohort ²⁰⁰	USA	Clinical informatics	Validation study, electronic medical record (EMR) analysis	Discover New Knowledge
22	2022	Uljarevic	Big Data Approach to Characterize Restricted and Repetitive Behaviors in Autism ¹⁹⁵	USA, Australia	Clinical informatics	Big data analysis, Repetitive Behavior Scale-Revised (RBS-R)	Discover New Knowledge
23	2022	Savickaite	The use of a tablet-based app for investigating the influence of autistic and ADHD traits on performance in a complex drawing task ²³⁹	UK	Clinical Research Informatics	Tablet-based drawing app, digital recording	Discover New Knowledge
24	2022	Varma	Identification of Social Engagement Indicators Associated With Autism Spectrum Disorder Using a Game-Based Mobile App: Comparative Study of Gaze Fixation and Visual Scanning Methods ²³⁷	USA	Clinical Research Informatics	Game-based mobile app, gaze fixation patterns, visual scanning methods, deep learning	Discover New Knowledge; Early Detection: Diagnostics/Screening Tool
25	2022	Yang	Pilot Randomized Control Trial of an App-Based CBT Program for Reducing Anxiety in Individuals with ASD without Intellectual Disability ²⁴⁰	South Korea	Consumer health informatics; Clinical Research Informatics	App-based cognitive behavioral therapy (CBT)	Intervention/Therapy Development
26	2022	Khadem-Reza	Evaluation of Brain Structure Abnormalities in Children with Autism Spectrum Disorder (ASD) Using Structural Magnetic Resonance Imaging ²⁸⁴	Iran	Imaging informatics	Structural magnetic resonance imaging (sMRI), feature extraction	Discover New Knowledge; Early Detection: Diagnostics/Screening Tool

27	2022	Kryszak	Clinician Perspectives on Telehealth Assessment of Autism Spectrum Disorder During the COVID-19 Pandemic ³⁰⁰	USA	Telehealth	Qualitative analysis, interviews	Interoperability/Sharing Information/Standards; Discover New Knowledge
28	2022	Ludwig	Telehealth Diagnosis of Autism Spectrum Disorder Through Clinical Cases ²⁹⁶	USA	Telehealth	Case series, telehealth diagnostic services	Interoperability/Sharing Information/Standards; Discover New Knowledge
29	2022	Reisinger	Provider and Caregiver Satisfaction with Telehealth Evaluation of Autism Spectrum Disorder in Young Children During the COVID-19 Pandemic ³⁰¹	USA	Telehealth	Telehealth evaluation, surveys	Interoperability/Sharing Information/Standards; Patient Education/Patient Engagement
30	2022	Nohelty	Effectiveness of Telehealth Direct Therapy for Individuals with Autism Spectrum Disorder ³⁰²	USA	Telehealth	Telehealth behavior therapy, nonconcurrent multiple baseline design	Patient Education/Patient Engagement
31	2021	Nabil	Applying machine learning on home videos for remote autism diagnosis: Further study and analysis ¹⁶⁹	Egypt	Clinical Informatics	Machine learning, Feature selection, Support Vector Machines, Backwards feature selection	Early Detection: Diagnostics/Screening Tool
32	2021	Mohanty	Identification of Autism Spectrum Disorder using Deep Neural Network ¹⁷⁰	India	Clinical Informatics	Deep Neural Networks (DNN), Principal Component Analysis (PCA)	Early Detection: Diagnostics/Screening Tool
33	2021	Failla	Using phecode analysis to characterize co-occurring medical conditions in autism spectrum disorders ¹⁹⁰	USA	Clinical Informatics	Phecode analysis, Phenome-Wide Association Study (PheWAS), logistic regression	Discover New Knowledge
34	2021	Tunç	Diagnostic shifts in autism spectrum disorder can be linked to early phenotypic profiles ²¹²	USA	Clinical Informatics	Machine learning, Support Vector Machine (SVM) classification	Discover New Knowledge
35	2021	Xipolitopoulos	Machine Learning for Autistic Spectrum Disorder Risk Screening ²⁰³	Greece	Clinical Informatics	Machine Learning Algorithms, Data Processing with Python Libraries, Application Development	Early Detection: Diagnostics/Screening Tool
36	2021	Feroe	Medication Use in the Management of Comorbidities Among Individuals With Autism Spectrum Disorder From a Large Nationwide Insurance Database ¹⁷⁴	USA	Clinical Informatics	Database analysis, statistical analysis	Discover New Knowledge
37	2021	Andrade	A Protocol for the Diagnosis of Autism Spectrum Disorder Structured in Machine Learning and Verbal Decision Analysis ²¹³	Brazil	Clinical Informatics	Machine learning, Random Forest, Verbal Decision Analysis	Discover New Knowledge
38	2021	Campbell	Improving Autism Screening and Referrals With Electronic Support and Evaluations in Primary Care ²¹⁶	USA	Clinical informatics	Electronic Health Record (EHR) modifications, automatic reminders, electronic screening tools	Interoperability/Sharing Information/Standards; Early Detection: Diagnostics/Screening Tool
39	2021	Wiratsin	Feature Selection Technique for Autism Spectrum Disorder ¹⁷⁵	Thailand	Clinical Informatics	Feature selection, Apriori algorithm, Support Vector Machine (SVM)	Discover New Knowledge
40	2021	Chang	Prevalence of Ophthalmologic Diagnoses in Children With Autism Spectrum Disorder Using the Optum Dataset: A Population-Based Study ¹⁷⁶	USA	Clinical informatics	Population-based retrospective cohort study, analysis of claims data	Discover New Knowledge
41	2021	Chen	Characteristics of sleep architecture in autism spectrum disorders: A meta-analysis based on polysomnographic research ¹⁷⁷	China	Clinical informatics	Meta-analysis, polysomnography	Discover New Knowledge

42	2021	Kriara	Beacon-Based Remote Measurement of Social Behavior in ASD Clinical Trials: A Technical Feasibility Assessment ²³⁵	Switzerland	Clinical Research Informatics	Bluetooth low energy (BLE) beacon-based algorithm, mobile application development	Discover New Knowledge
43	2021	Oliveira	Computer-aided autism diagnosis based on visual attention models using eye tracking ²⁴²	Brazil	Clinical Research Informatics	Eye tracking, visual attention models, machine learning, neural networks	Discover New Knowledge; Case Identification/Database Infrastructure
44	2021	Chang	Computational Methods to Measure Patterns of Gaze in Toddlers With Autism Spectrum Disorder ²³⁶	USA	Clinical Research Informatics	Computational vision analysis, mobile app development	Early Detection: Diagnostics/Screening Tool
45	2021	Penev	A Mobile Game Platform for Improving Social Communication in Children with Autism: A Feasibility Study ²⁶⁰	USA	Consumer Health Informatics	Mobile game-based therapy, qualitative feedback collection	Intervention/Therapy Development
46	2021	Zorcec	Enriching Human-Robot Interaction with Mobile App in Interventions of Children with Autism Spectrum Disorder ²⁵²	Macedonia, Croatia, UK, Israel	Consumer health informatics	Mobile applications, humanoid robot interaction	Intervention/Therapy Development
47	2021	De Luca	Innovative Use of Virtual Reality in Autism Spectrum Disorder: A Case-Study ²⁵³	Italy	Consumer health informatics	Virtual reality (VR) training, Cognitive-Behavioral Therapy (CBT)	Intervention/Therapy Development
48	2021	Tawhid	A Spectrogram Image-Based Intelligent Technique for Automatic Detection of Autism Spectrum Disorder from EEG ²⁷⁶	Australia, Saudi Arabia	Imaging Informatics	Machine learning, deep learning, EEG spectrogram images	Discover New Knowledge; Early Detection: Diagnostics/Screening Tool
49	2021	Huang	Identifying Autism Spectrum Disorder From Resting-State fMRI Using Deep Belief Network ²⁸³	Hong Kong, China	Imaging Informatics	Deep belief network (DBN), graph-based feature selection, resting-state fMRI	Discover New Knowledge; Early Detection: Diagnostics/Screening Tool
50	2021	Kølves	Assessment of Suicidal Behaviors Among Individuals With Autism Spectrum Disorder in Denmark ³²	Denmark	Public health informatics	National register data analysis	Discover New Knowledge
51	2021	Morito	Development of YOUNCHART the Information Sharing System for Linking Children with Autism Spectrum Disorder, Their Families, and Supporters ²⁵¹	Japan	Consumer Health Informatics	Application software development, User feedback integration	Patient Education/Patient Engagement; Reduce Health Disparities
52	2021	Cantin-Garside	Understanding the experiences of self-injurious behavior in autism spectrum disorder: Implications for monitoring technology design ²⁸⁷	USA	Public health informatics	Qualitative content analysis, interviews, focus groups	Patient Education/Patient Engagement; Discover new knowledge
53	2021	Rezae	Public transport planning tool for users on the autism spectrum: from concept to prototype ²⁶²	Australia	Public health informatics; Consumer Health Informatics	Mobile application development, participatory design, user surveys	Patient Education/Patient Engagement; Intervention/Therapy Development
54	2021	Sivaraman	Telehealth mask-wearing training for children with autism during the COVID-19 pandemic ²⁹⁴	Belgium, India, Mexico, Costa Rica	Telehealth	Video-calling, telehealth coaching	Intervention/Therapy Development
55	2021	Sutantio	Validity of Telemedicine for Diagnosing Autism Spectrum Disorder: Protocol-Guided Video Recording Evaluation ²⁹⁵	Indonesia	Telehealth	Telemedicine, protocol-guided video recording	Early Detection: Diagnostics/Screening Tool
56	2021	McCrae	Telehealth cognitive behavioral therapy for insomnia in children with autism spectrum	USA, Hong Kong	Telehealth	Telehealth delivery of cognitive behavioral therapy	Intervention/Therapy Development

			disorder: A pilot examining feasibility, satisfaction, and preliminary findings ²⁹⁹				
57	2020	Peng	Natural language processing (NLP) tools in extracting biomedical concepts from research articles: a case study on autism spectrum disorder ¹⁸²	USA	Clinical informatics	Comparative analysis of NLP tools (CLAMP, cTAKES, MetaMap) for extracting ASD-specific terminology	Discover New Knowledge; Case Identification/Database Infrastructure
58	2020	Li	Network analysis of autistic disease comorbidities in Chinese children based on ICD-10 codes ²⁰²	China	Clinical informatics	FP-growth algorithm, disease network analysis using Cytoscape	Discover New Knowledge
59	2020	Ptomey	Weight status and associated comorbidities in children and adults with Down Syndrome, Autism Spectrum Disorder, and Intellectual and Developmental Disabilities ¹⁸³	USA	Clinical informatics	Data analysis from HERON database	Discover New Knowledge; Reduce Health Disparities
60	2020	Thabtah	A New Machine Learning Model for Autism Detection ¹⁸⁹	UK	Clinical informatics	Machine learning model (Rules-Machine Learning) for autism detection	Discover New Knowledge
61	2020	Mazurek	Effectiveness of the Extension for Community Health Outcomes Model as Applied to Primary Care for Autism ²²⁷	USA	Clinical informatics	Technology-based training model evaluation	Reduce Health Disparities
62	2020	Rieske	Parental Age at Conception and the Relationship with Severity of Autism Symptoms ²⁴¹	USA	Clinical Research Informatics	Statistical analysis of clinical data	Discover New Knowledge
63	2020	Billing	The DREAM Dataset: Supporting a data-driven study of autism spectrum disorder and robot enhanced therapy ²³¹	Sweden; UK	Clinical Research Informatics, Consumer Health Informatics	Data collection during Robot Enhanced Therapy (RET) sessions, with sensory data processing for behavior analysis	Discover New Knowledge
64	2020	Barbaro	Study protocol for an evaluation of ASDetect - a Mobile application for the early detection of autism ²⁵⁸	Australia	Consumer health informatics	Mobile application (ASDetect) based on the Social Attention and Communication Surveillance (SACS) tool	Early Detection: Diagnostics/Screening Tool
65	2020	Koumpouros	User-centered design and assessment of a wearable application for children with Autistic Spectrum Disorder supporting daily activities ²⁷³	Greece	Consumer health informatics	User-centered design, wearable application development, subjective evaluation	Intervention/Therapy Development
66	2020	Rabba	Development of a Web-Based Resource for Parents of Young Children Newly Diagnosed With Autism: Participatory Research Design ²⁵⁶	Australia	Consumer health informatics	Participatory action research (PAR)	Patient Education/Patient Engagement; Intervention/Therapy Development
67	2020	Martins	Audiovisual Media Content Preferences of Children with Autism Spectrum Disorders: Insights from Parental Interviews ²⁶¹	USA	Consumer health informatics	Qualitative analysis, thematic analysis	Discover New Knowledge; Patient Education/Patient Engagement
68	2020	Bellon-Ham	Twitter Usage About Autism Spectrum Disorder ²⁸⁶	USA	Public health informatics	Cross-sectional analysis of Twitter data	Discovering new knowledge; Patient Education/Patient Engagement
69	2020	Rakić	Improving the Detection of Autism Spectrum Disorder by Combining Structural and Functional MRI Information ²⁸²	Spain	Imaging informatics	Combination of structural and functional MRI data using machine learning (stacked autoencoders and multilayer perceptions)	Discover New Knowledge, Case Identification/Database Infrastructure
70	2020	Ameis	Coping, resilience, and support systems for autistic individuals and families during the COVID-19 pandemic ²⁹³	Canada	Telehealth	Commentary and review of current practices	Patient Education/Patient Engagement

71	2020	Constantino	Timing of the Diagnosis of Autism in African American Children ²⁸⁸	USA	Public health informatics	Analysis of diagnostic odysseys for African American children with ASD	Reduce Health Disparities, Case Identification/Database Infrastructure
72	2019	Ewen	Epilepsy and Autism Severity: A Study of 6,975 Children ¹⁸⁵	USA	Clinical Informatics	Patient registry database, Regression	Discover New Knowledge
73	2019	Hoover	The Interactive Trauma Scale: A Web-Based Measure for Children with Autism ²¹⁵	USA	Clinical Informatics	Web-Based Assessment, Touchscreen Interaction, User Satisfaction Questionnaires	Intervention/Therapy Development
74	2019	Stevens	Identification and analysis of behavioral phenotypes in autism spectrum disorder via unsupervised machine learning ²⁰¹	USA	Clinical Informatics	Machine Learning, Cluster Analysis	Discover New Knowledge
75	2019	Downs	Effect of a Computer-Based Decision Support Intervention on Autism Spectrum Disorder Screening in Pediatric Primary Care Clinics ²²²	USA	Clinical Informatics	Computer-Based Decision Support	Early Detection: Diagnostics/Screening Tool
76	2019	Lombardo	Big data approaches to decomposing heterogeneity across the autism spectrum ¹⁹³	UK	Clinical Informatics	Big Data Analysis	Discover New Knowledge
77	2019	Shields	Self-Injurious Behavior Among Adults With ASD: Hospitalizations, Length of Stay, and Costs of Resources to Deliver Care ²²⁴	USA	Clinical informatics	Statistical analysis of hospital discharge records	Reduce Health Disparities
78	2019	Omar	A Machine Learning Approach to Predict Autism Spectrum Disorder ¹⁸⁸	Bangladesh	Clinical informatics	Machine learning algorithms (Random Forest-CART, Random Forest-ID3)	Early Detection: Diagnostics/Screening Tool; Discover New Knowledge
79	2019	Printz	Morbidity after tonsillectomy in children with autism spectrum disorders ²²⁵	USA	Clinical Informatics	Retrospective cohort study, statistical analysis using Kids' Inpatient Database	Reduce Health Disparities
80	2019	Pulmano	MIND Plug-in: Development of an Electronic Medical Record based data collection tool for research in autism and neurodevelopmental disorders ¹⁷³	Philippines	Clinical informatics	Development of an EMR plug-in	Case Identification/Database Infrastructure
81	2019	Ness	An Observational Study With the Janssen Autism Knowledge Engine (JAKE®) in Individuals With Autism Spectrum Disorder ²⁴⁶	USA	Clinical Research Informatics	Janssen Autism Knowledge Engine (JAKE®) Sensory biomarkers	Discover New Knowledge
82	2019	Little	Automated Measures to Understand Communication Opportunities for Young Children With Autism in the Community: A Pilot Study ²³⁴	USA	Clinical Research Informatics	Automated objective measures (Language ENvironmental Analysis - LENA system™ and Global Positioning System - GPS)	Discover New Knowledge
83	2019	Masino	m-Health and Autism: Recognizing Stress and Anxiety with Machine Learning and Wearables Data ²⁷²	USA	Consumer Health Informatics	Machine Learning, Wearable Technology	Intervention/Therapy Development
84	2019	Parsons	Appropriateness of the TOBY Application an iPad Intervention for Children with Autism Spectrum Disorder: A Thematic Approach ²⁶⁴	Australia	Consumer health informatics	Qualitative thematic analysis of interviews	Intervention/Therapy Development
85	2019	Khullar	IoT based assistive companion for hypersensitive individuals (ACHI) with autism spectrum disorder ²⁵⁷	India	Consumer health informatics	IoT, fuzzy inference system	Intervention/Therapy Development
86	2019	Rosenbloom	The Effects of a Technology-Based Self-monitoring Intervention on On-Task Disruptive	USA	Consumer Health Informatics	Self-monitoring, Handheld Computer-Based Technology	Patient Education/Patient Engagement

			and Task-Completion Behaviors for Adolescents with Autism ²⁶³				
87	2019	Eill	Functional Connectivities Are More Informative in Diagnostic Classification of Autism ²⁷⁵	USA	Imaging Informatics	Machine Learning, Functional Connectivity MRI	Early Detection: Diagnostics/Screening Tool
88	2019	Sutherland	Telehealth and autism: Are telehealth language assessments reliable and feasible for children with autism? ²⁹²	Australia	Telehealth	Telehealth, Language Assessment, Surveys	Intervention/Therapy Development
89	2018	Bishop-Fitzpatrick	Using machine learning to identify patterns of lifetime health problems in decedents with autism spectrum disorder ¹⁷²	USA	Clinical Informatics	Electronic Health Records (EHR), Machine Learning	Discover New Knowledge
90	2018	Gordon-Lipkin	Anxiety and mood disorder in children with autism spectrum disorder and ADHD ¹⁸⁶	USA	Clinical Informatics	Online Database, Generalized Linear Model	Discover New Knowledge
91	2018	Sadouk	A Novel Deep Learning Approach for Recognizing Stereotypical Motor Movements within and across Subjects on the Autism Spectrum Disorder ²⁰⁶	Morocco	Clinical Informatics	Clinical Decision Support, Wireless accelerometer, Deep learning	Early Detection: Diagnostics/Screening Tool
92	2018	Thabtah	A new computational intelligence approach to detect autistic features for autism screening ²¹⁹	UK	Clinical Informatics	Variable Analysis (VA), Computational intelligence approach	Early Detection: Diagnostics/Screening Tool
93	2018	Thabtah	An Accessible and Efficient Autism Screening Method for Behavioural Data and Predictive Analyses ¹⁹⁴	New Zealand	Clinical informatics	Machine learning algorithms (Naïve Bayes, Logistic Regression) for predictive analysis	Early Detection: Diagnostics/Screening Tool; Case Identification/Database Infrastructure
94	2018	Zhang	Analysis of gut microbiota profiles and microbe-disease associations in children with autism spectrum disorders in China. ²³⁰	China	Clinical Research Informatics	Multiple sequence clustering operational taxonomic units (OTUs)	Discover New Knowledge
95	2018	Feczko	Subtyping cognitive profiles in Autism Spectrum Disorder using a Functional Random Forest algorithm ²²⁸	USA	Clinical Research Informatics; Imaging Informatics	Random Forest Algorithm, Precision Medicine, MRI brain biomarkers	Discover New Knowledge
96	2018	Chukoskie	A Novel Approach to Training Attention and Gaze in ASD: A Feasibility and Efficacy Pilot Study ²⁴⁸	USA	Consumer Health Informatics	Assistive technologies	Intervention/Therapy Development
97	2018	Khan	Mobile Aid to Assist with Care Decisions in Children with Autism Spectrum Disorder (ASD) ²⁷¹	USA	Consumer health informatics	MyHeifer mobile application for easing caregiver burden	Patient Education/Patient Engagement
98	2018	Heinsfeld	Identification of autism spectrum disorder using deep learning and the ABIDE dataset ²⁷⁸	Brasil	Imaging Informatics	Deep Learning	Early Detection: Diagnostics/Screening Tool
99	2018	Bolton	Brain dynamics in ASD during movie-watching show idiosyncratic functional integration and segregation ²⁷⁷	Switzerland	Imaging Informatics	inter-subject functional correlation (ISFC), ANOVA	Discover New Knowledge
100	2018	Abbas	Machine learning approach for early detection of autism by combining questionnaire and home video screening ²⁹⁷	USA	Telehealth	Video screening, Machine learning	Early Detection: Diagnostics/Screening Tool

101	2017	Yuan	Autism spectrum disorder detection from semi-structured and unstructured medical data ²⁰⁷	USA	Clinical Informatics	Data Mining, Optical Character Recognition (OCR), Machine Learning, Natural Language Processing (NLP)	Early Detection: Diagnostics/Screening Tool
102	2017	Campbell	Use of a Digital Modified Checklist for Autism in Toddlers - Revised with Follow-up to Improve Quality of Screening for Autism ²⁰⁸	USA	Clinical Informatics	Digital Form, Electronic Health Record (EHR)	Early Detection: Diagnostics/Screening Tool
103	2017	Bush	Extracting autism spectrum disorder data from the electronic health record ¹⁹⁷	USA	Clinical Informatics	Data Mining, Electronic Health Record (EHR)	Case Identification/Database Infrastructure
104	2017	Vargas-Cuentas	Developing an eye-tracking algorithm as a potential tool for early diagnosis of autism spectrum disorder in children ²²⁰	Peru	Clinical Informatics	Tablet-based eye-tracking algorithm	Early Detection: Diagnostics/Screening Tool
105	2017	Downs	Detection of Suicidality in Adolescents with Autism Spectrum Disorders: Developing a Natural Language Processing Approach for Use in Electronic Health Records ¹⁸⁷	USA	Clinical Informatics	Natural Language Processing (NLP), Electronic Health Record (EHR), Classification	Discover New Knowledge
106	2017	Whitehouse	A randomised controlled trial of an iPad-based application to complement early behavioural intervention in Autism Spectrum Disorder ²²⁹	Australia	Clinical Research Informatics	Randomized Control Trial, Mobile Application	Intervention/Therapy Development
107	2017	Lung	Urban and Education Disparity for Autism Spectrum Disorders in Taiwan Birth Cohort Study ²⁹⁰	Taiwan	Public Health Informatics	Health disparities, Digital Form	Early Detection: Diagnostics/Screening Tool
108	2016	Sturner	Autism Screening With Online Decision Support by Primary Care Pediatricians Aided by M-CHAT/F ²⁰⁹	USA	Clinical Informatics	Digital form, Electronic Health Record	Early Detection: Diagnostics/Screening Tool
109	2016	Bone	Use of machine learning to improve autism screening and diagnostic instruments: effectiveness, efficiency, and multi-instrument fusion ²¹⁰	USA	Clinical Informatics	Machine Learning, Screener Algorithm	Early Detection: Diagnostics/Screening Tool
110	2016	Lingren	Electronic Health Record Based Algorithm to Identify Patients with Autism Spectrum Disorder ¹⁷¹	USA	Clinical Informatics	Data Mining, Electronic Health Record (EHR), Machine Learning, Natural Language Processing (NLP)	Case Identification/Database Infrastructure
111	2016	Maenner	Development of a Machine Learning Algorithm for the Surveillance of Autism Spectrum Disorder ¹⁹⁶	USA	Clinical Informatics	Electronic Health Record (EHR), Machine learning, Bag-of-words approach, Random forests	Case Identification/Database Infrastructure
112	2016	Schuler	Discovering Patient Phenotypes Using Generalized Low Rank Models ¹⁹¹	USA	Clinical Informatics	Phenotype, Natural Language Processing (NLP), Generalized Low Rank Modeling (GLRM), Electronic Health Record (EHR)	Discover New Knowledge
113	2016	AI-Jabery	Ensemble Statistical and Subspace Clustering Model for Analysis of Autism Spectrum Disorder Phenotypes ¹⁹²	USA	Clinical Informatics	Electronic Health Record (EHR), Machine Learning, Phenotype, clustering	Discover New Knowledge
114	2016	Anzulewicz	Toward the Autism Motor Signature: Gesture patterns during smart tablet gameplay identify children with autism ²¹⁸	Poland	Clinical Informatics	Clinical Decision Support System (CDSS), Mobile application	Early Detection: Diagnostics/Screening Tool
115	2016	Sharpe	A Dichotomy of Information-Seeking and Information-Trusting: Stem Cell Interventions	Canada	Consumer Health Informatics	Information Seeking Behavior, Social/Cognitive Study	Patient Education/Patient Engagement

			and Children with Neurodevelopmental Disorders ²⁷⁰				
116	2016	Bush	Exploring perceptions and use of the electronic health record by parents of children with autism spectrum disorder: A qualitative study ²⁶⁵	USA	Consumer Health Informatics	Electronic Health Record (EHR), Social/Cognitive Science	Patient Education/Patient Engagement
117	2016	Saha	Modeling social support in autism community on social media ²⁶⁷	USA	Consumer Health Informatics	Social Media Information	Patient Education/Patient Engagement
118	2016	Zheng	Robot-Mediated Imitation Skill Training for Children With Autism ²⁴⁷	USA	Consumer Health Informatics	Robotics	Intervention/Therapy Development
119	2016	Fletcher-Watson	A trial of an iPad™ intervention targeting social communication skills in children with autism ²⁵⁰	UK	Consumer Health Informatics	Mobile Application	Intervention/Therapy Development
120	2016	Linstead	AMP: A Platform for Managing and Mining Data in the Treatment of Autism Spectrum Disorder ²⁶⁹	USA	Consumer Health Informatics	Personal Health Record, Mobile Application, Web client, Analytics engine, Secure data repository	Interoperability/Sharing Information/Standards
121	2016	Ghiassian	Using Functional or Structural Magnetic Resonance Images and Personal Characteristic Data to Identify ADHD and Autism ²⁸⁰	Canada	Imaging Informatics	Learning algorithm	Early Detection: Diagnostics/Screening Tool
122	2016	Xiao	Diagnostic model generated by MRI-derived brain features in toddlers with autism spectrum disorder ²⁸¹	China	Imaging Informatics	Machine learning, Random forest Algorithm	Early Detection: Diagnostics/Screening Tool
123	2016	Brooks	Implementation of Web-Based Autism Screening in an Urban Clinic ²⁹¹	USA	Public Health Informatics	Health disparities, Mobile Application, Web-based interface	Early Detection: Diagnostics/Screening Tool
124	2015	Bone	Applying machine learning to facilitate autism diagnostics: pitfalls and promises ²¹¹	USA	Clinical Informatics	Machine Learning	Early Detection: Diagnostics/Screening Tool
125	2015	Mugzach	An ontology for Autism Spectrum Disorder (ASD) to infer ASD phenotypes from Autism Diagnostic Interview-Revised data ⁶⁴	Israel	Clinical Informatics	Ontology, Phenotype	Case Identification/Database Infrastructure
126	2015	Bauer	Computer decision support changes physician practice but not knowledge regarding autism spectrum disorders ¹¹⁵	USA	Clinical Informatics	Clinical Decision Support System (CDSS)	Early Detection: Diagnostics/Screening Tool
127	2015	Mohd Roffeii	Seeking social support on Facebook for children with Autism Spectrum Disorders (ASDs) ²⁶⁸	Malaysia	Consumer Health Informatics	Social Media Information	Patient Education/Patient Engagement
128	2015	Jin	Identification of infants at high-risk for autism spectrum disorder using multiparameter multiscale white matter connectivity networks ²⁷⁹	USA	Imaging Informatics	Machine learning, Multikernel support vector, machine classification framework	Early Detection: Diagnostics/Screening Tool
129	2014	Angell	The social life of health records: Understanding families' experiences of autism ²⁶⁶	USA	Consumer Health Informatics	Electronic Health Record (EHR), Social/Cognitive Science, Health Disparities	Reduce Health Disparities
130	2013	Doshi-Velez	Comorbidity Clusters in Autism Spectrum Disorders: An Electronic Health Record Time-Series Analysis ¹⁰	USA	Clinical Informatics	Electronic Health Record (EHR), Data Mining, i2b2, Phenotype-wide association study	Discover New Knowledge

131	2013	McCray	Modeling the Autism Spectrum Disorder Phenotype ¹⁹⁸	USA	Clinical Informatics	Phenotype ontology	Case Identification/Database Infrastructure
132	2013	Lahiri	Design of a virtual reality based adaptive response technology for children with autism ²⁴⁹	India	Consumer Health Informatics	Assistive technologies, Virtual reality (VR) interactive system	Intervention/Therapy Development
133	2013	Kaufmann	Brief report: CANTAB performance and brain structure in pediatric patients with Asperger Syndrome ²⁸⁵	Australia	Imaging Informatics	Regression Analysis	Discover New Knowledge
134	2013	Reese	Evaluating Interactive Videoconferencing for Assessing Symptoms of Autism ²⁹⁸	USA	Telehealth	Videoconference Assessment, Health disparities	Reduce Health Disparities
135	2012	Kohane	The co-morbidity burden of children and young adults with autism spectrum disorders ⁷	USA	Clinical Informatics	Electronic Health Record (EHR), Data Mining, Phenotype-wide association study	Discover New Knowledge
136	2012	Wall	Use of Artificial Intelligence to Shorten the Behavioral Diagnosis of Autism ²²¹	USA	Clinical Informatics	Artificial Intelligence	Early Detection: Diagnostics/Screening Tool
137	2012	Anderson	Occurrence and family impact of elopement in children with autism spectrum disorders ²³	USA	Clinical Informatics	Online Database, Statistical Analysis	Reduce Health Disparities
138	2011	Goodwin	Automated Detection of Stereotypical Motor Movements ²²³	USA	Clinical Informatics	Clinical Decision Support, Wireless accelerometer, Pattern recognition algorithms	Early Detection: Diagnostics/Screening Tool
139	2010	Johnson	Using global unique identifiers to link autism collections ²¹⁷	USA	Clinical Informatics	Global Unique Identifiers, Interoperability, Standards	Case Identification/Database Infrastructure; Interoperability/Sharing Information/Standards
140	2009	Hertz-Picciotto	The rise in autism and the role of age at diagnosis ¹⁸⁴	USA	Clinical Informatics	Database; Descriptive statistics	Discover New Knowledge

Appendix B

Condition Codes & Groupings

Diagnosis	Clinical Classifications Software Refined (CCSR) Codes	PheCodes	Notes
	https://hcup-us.ahrq.gov/toolssoftware/ccsr/ccs_refined.jsp	https://phewascatalog.org/phecodes_icd10cm	
Attention-Deficit/Hyperactivity Disorder (ADHD)		313.1	
Adjustment Reaction	MBD007	304	
Allergic reactions	INJ031		Allergies, eczema, dermatitis
Anxiety	MBD005	300; 300.1; 300.11; 300.12; 300.13; 300.2; 300.3; 300.4; 300.8; 300.9 (300-300.9)	Anxiety, panic disorder, separation anxiety disorder, social phobia
Autism Spectrum Disorder (ASD)		313.3	
Asthma	RSP009	495; 495.1; 495.11; 495.2	
Cancer			
Chromosomal Abnormalities	MAL009	758; 758.1	
Conduct Disorders	MBD008	312; 312.3	Conduct disorder; oppositional defiant disorder; impulse disorder; explosive disorder
Congenital Anomalies	MAL010	755; 755.1; 755.3; 755.4; 755.6; 755.61; 756	Congenital malformations
Constipation	DIG025	5563	
Depression	MBD002	296.2; 296.22	Major depressive disorder; dysthymic disorder; depression
Developmental Delays		315	
Diabetes	END003-END006	249-250	
Disruptive Mood Dysregulation Disorder	MBD004	296	
Eating Disorder	MBD010	305.2; 305.21	
Epilepsy; Seizures	NVS009	345; 345.1; 345.11; 345.12; 345.3	
Esophageal Disorders	DIG004	530.11	Gastro-esophageal reflux disease (GERD), eosinophilic esophagitis
Headache/Migraine	NVS010	339; 340	
Hearing loss	EAR004	389	

Intellectual or Developmental Disability (IDD)		315.3	
Learning Disorders		315.1	
Muscle disorders	MUS026		Muscle disorders; muscle weakness, muscle spasm
Musculoskeletal Congenital Conditions	MAL008		Macrocephaly, plagiocephaly, congenital malformities, etc.
Nervous System Disorders	NVS006		Restless leg syndrome; movement disorders; Huntington's disease
Neuromuscular Disorders		333.4; 335; 342; 343; 358; 358.1; 359.1; 359.2	
Nutritional Deficiency	END007	261; 261.1; 261.2; 261.3; 261.4; 262; 263	
Obesity	END009	278; 278.1; 278.11	
Obsessive-compulsive disorder (OCD)	MBD006	300.3	
PTSD/Acute Stress Reaction	MBD007	300.8; 300.9	
Schizophrenia/ Psychotic Disorders	MBD001	295; 295.1; 295.2; 295.3	
Sleep Disorder	NVS016	327; 327.1; 327.4; 327.41; 327.5; 327.6; 327.7; 327.71	Sleep disorder, insomnia, hypersomnia, sleep apnea, night terrors
Speech/Language Disorders		315.2	
Strabismus	EYE007		Strabismus: esotropia, exotropia, etc
Substance Use Disorder		316; 316.1; 317; 317.1	
Suicidal Thoughts and Behaviors (STB)	MBD012	297; 297.1; 297.2	Suicidal ideation/attempt/intentional self-harm
Symptoms: Abdominal pain; Digestive	SYM006	785	Abdominal pain, epigastric pain, gas pain, upper and lower quadrant pain, diarrhea, abdominal distention
Symptoms: Malaise and fatigue	SYM007		
Symptoms: Mental/Substance Use Conditions	SYM008		Signs and symptoms involving appearance and behavior; restlessness, agitation, hostility, irritability, impulsiveness, violent behavior, homicidal ideations
Symptoms: Nervous system	SYM010		Lack of coordination, symbolic dysfunctions, attention and concentration deficit, altered mental status, involuntary movements, dysarthria, tremor, apraxia, ataxia, abnormal reflex, difficulty walking/unsteadiness,

			cognitive decline/cognitive function and awareness, disorientation, facial weakness, slurred speech
Teeth and Gingiva Disorders	DIG002		Dental caries; tooth erosion, tooth abscess, etc.
Tics/Stuttering		313.2	
Urinary Incontinence	GEN008		
Vitamin Deficiency		261; 261.1; 261.2; 261.3; 261.4; 262	
Utilization			
Abnormal Findings without Diagnosis	SYM017		Abnormal EEG; abnormal EKG; prediabetes; abnormal blood chemistry, specimen, mineral
Fluid and Electrolyte Disorders	END011		Dehydration; acidosis
Lifestyle/Life Management Factors	FAC020		Other problems related to lifestyle
Otitis Media	EAR001		
Socioeconomic/Psychosocial Factors	FAC019		Psychosocial problems; social exclusion/rejection; target of (perceived) discrimination/persecution
Symptoms: Circulatory	SYM012		Cardiac murmur, tachycardia, palpitations, bradycardia, hemorrhage
Symptoms: Fever	SYM002		
Symptoms: Nausea and vomiting	SYM004		
Symptoms: Respiratory	SYM013		Cough, congestion, throat pain, wheezing, shortness of breath, dyspnea, tachypnea
Symptoms: Skin/Subcutaneous	SYM014		Rash, swelling, etc.
Viral infection	INF008		Viral infections, RSV, acute bronchitis, Fifth's Disease, etc.

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Portions of this document were edited for grammar, style, and clarity using Grammarly⁴⁵⁰ and OpenAI's⁴⁵¹ generative AI tools. These tools assisted solely in the editing process, without contributing to the original content creation.

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