Multimodal and Agentic AI for Cognitive Accessibility and Linguistic Preservation

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Abstract

Artificial Intelligence (AI) has become a transformative tool in enhancing cognitive accessibility and preserving linguistic heritage. This thesis investigates the convergence of Generative AI (Gen AI), multimodal learning, and agentic AI to address challenges such as language learning and communication deficits faced by neurodivergent individuals, particularly those with Autism Spectrum Disorder (ASD), while simultaneously contributing to the preservation of endangered and lost languages in minority communities.

This research adopts a multi-faceted approach. First, it conducts a comprehensive literature review and technical analysis of multimodal AI applications for ASD clinical practices. Second, it designs and tests Gen AI tools, including Large Language Models (LLMs), for autism therapies and interactive social learning. Third, it examines the linguistic, cultural, and technical challenges of preserving endangered languages and proposes the Revitalization Framework of Linguistic Heritage (RFLH)—a Gen AI approach for reconstructing lost languages. Finally, it develops the Auto DB Agent, an agentic self-improving system capable of interpreting natural languages and generating SQL queries in dynamic database environments, lowering the barriers for non-technical users in healthcare and cultural data analysis.

By synthesizing these interconnected fields, this research contributes to human-centered AI design, expanding the accessibility of information and computational systems. The outcomes of this study have implications for education, historical linguistics, human-computer interaction, and AI-driven cognitive support, paving the way for more inclusive and intelligent AI systems that bridge the gap between digital information and diverse human needs.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Chapter 1

Introduction

1.1 Background and Motivation

Artificial Intelligence (AI) has rapidly evolved as a transformative innovation in addressing complex societal and cultural issues. In recent years, Multimodal AI—which combines text, vision, and speech data—has demonstrated remarkable capabilities in fields such as clinical assessment, therapeutic interventions, and semantic representation of knowledge (John, 2023; Munikoti et al., 2024). In parallel, agentic AI pushes beyond conventional machine learning paradigms by enabling systems to make autonomous decisions and adapt in real time (Viswanathan, 2025; Xiong, 2024). This confluence of multimodal and agentic methods has opened new frontiers for tackling significant challenges in cognitive accessibility and linguistic heritage preservation (Durante et al., 2024; Singh et al., 2025; Xiong et al., 2024).

Cognitive Accessibility: Among neurodivergent populations, individuals with Autism Spectrum Disorder (ASD) often encounter profound difficulties in social communication, repetitive behaviors, and sensory integration (Alasmari et al., 2024; Bader et al., 2022). Researchers have introduced a range of AI-driven interventions—such as generative language models that scaffold social scripts or conversational skills—to help mitigate these barriers (Choi et al., 2024; Feng et al., 2024; Haroon & Dogar, 2024). Social robots equipped with advanced multimodal perception have also shown promise in improving engagement and interactive learning among children with ASD (Kian et al., 2024; Mishra & Welch, 2024). Collectively, these systems aim to reduce the cognitive load of traditional interventions, offering more personalized and dynamic therapeutic experiences (Fuentes-Álvarez et al., 2023; Shemy et al., 2024; Wang et al., 2022).

Linguistic Heritage: In the cultural preservation space, more than half of the world's 7,000+ languages are predicted to vanish by the end of the century (Hutson et al., 2024; Pinhanez, 2024). As linguistic identity is closely linked to cultural legacy and community resilience, the disappearance of languages represents not merely the loss of a communication system but also the erosion of intangible heritage (Bromham et al., 2021; Indigenous Languages, 2023). Large Language Models (LLMs), adept at extrapolating from limited data, offer tools to revitalize endangered or lost languages through corpus augmentation, reconstruction of grammar, and generation of contextual materials (Pinhanez, 2024; Shu et al., 2024; Yang et al., 2024). AI-driven efforts not only help preserve linguistic diversity but also empower local communities to maintain their cultural narratives (Reviving Indigenous Languages Using Machine Learning, 2024).

While generative and multimodal methods address the content and modality aspects, agentic AI provides sophisticated automation capabilities that streamline access to structured data (Spencer & Kongborrirak, 2024). Traditional database operations require substantial technical expertise, often creating barriers for healthcare providers, educators, or communities seeking quick insights (Singh et al., 2025; Wang et al., 2024). By leveraging Text2SQL technology within an agentic AI framework, users can pose natural language queries—such as "Show me therapy outcomes by age group"—without knowledge of query syntax (Li et al., 2024; Pourreza et al., 2024; Zhu et al., 2024). This democratization of data retrieval is especially powerful where real-time decisions or data explorations are integral to academic, healthcare, or cultural applications (Conroy, 2023; Lee et al., 2023; Moor et al., 2023).

Within this thesis, several core themes emerge, each representing a critical dimension of how AI can serve as an enabling force:

- Multimodal AI for Clinical Analysis of ASD: Integrating speech, visual cues, and text for more accurate clinical analysis (Artsi et al., 2024; Rouzbahani & Karimipour, 2024).
- Gen AI for ASD: Targeting personalized therapy and educational applications (Bhuyan et al., 2025; Guettala et al., 2024).
- AI for Lost Language Preservation: Utilizing generative LLMs to reconstruct, revitalize, and archive languages at risk (Reviving Indigenous Languages Using Machine Learning, 2024; Yang et al., 2024).
- Agentic AI for Text2SQL: Developing self-improving agents that automate complex database queries and reduce the technical overhead required for data access (Rebei, 2023; Wang et al., 2024).

By interweaving these themes, this research aspires to highlight a unified AI ecosystem where adaptive, multimodal, and generative tools collectively promote cognitive accessibility and safeguard linguistic heritage (Hutson et al., 2024; Xia et al., 2024b; Multimodal LLMs in Health Care: Applications, Challenges, and Future Outlook, 2024). This integrated approach supports diverse user needs—ranging from clinical practitioners assisting ASD individuals to linguistic communities striving to preserve cultural identity. It also exemplifies how cutting-edge AI can serve broader societal objectives when guided by inclusive design and ethical considerations (Choi et al., 2024; Roshanaei et al., 2023; Washington & Wall, 2023; Zhang & Wang, 2024).

1.2 Problem Statement

Despite significant progress in AI research, four major challenges persist that hinder the broader impact of multimodal, agentic, and generative systems on cognitive accessibility and linguistic preservation.

1.2.1 Diverse Data Requirements

Cognitive accessibility interventions for Autism Spectrum Disorder (ASD) and the preservation of endangered languages both depend on robust, multimodal datasets incorporating text, audio, and visual elements (Nanduri & Bonsignore, 2023; Smart et al., 2024). However, these datasets are frequently scarce, fragmented, or lack a standardized format, making it difficult to train and validate AI models effectively (Leng et al., 2024; Pattnayak et al., 2024). In ASD-related studies, high-quality datasets that capture nuanced behaviors, such as facial expressions, speech patterns, and social interactions, are especially difficult to assemble due to privacy concerns and the high resource demands of clinical data collection (Abbas et al., 2018; Carpenter et al., 2020; Rouzbahani & Karimipour, 2024). Similarly, for linguistic preservation, dwindling speaker populations and minimal archival records constrain efforts to build sufficiently large corpora necessary for modern AI-driven language modeling (Pinhanez, 2024; Smart et al., 2024).

1.2.2 Lack of Accessibility

Even when AI solutions exist, neurodivergent individuals and communities seeking to safeguard their linguistic heritage often encounter significant usability barriers (Chemnad & Othman, 2024; Hutson et al., 2024). Many current technologies require specialized technical expertise or rigid interaction protocols that do not accommodate a variety of cognitive styles (Pinhanez, 2024). Consequently, individuals with ASD may struggle to use AI-driven therapy tools that lack intuitive interfaces or flexible modes of input (Chan & Tsi, 2023; Chistol et al., 2023). Likewise, communities aiming to revitalize endangered languages often lack the necessary training or infrastructure to leverage advanced computational tools (Chan & Tsi, 2023; Reviving Indigenous Languages Using Machine Learning, 2024). This accessibility gap underscores the need for AI interfaces designed with inclusive principles and effortless user engagement in mind (Nanduri & Bonsignore, 2023; Yang et al., 2024).

1.2.3 Agentic Framework Gaps

While LLMs can generate effective text outputs, many Text2SQL solutions remain brittle in real-world environments (Katsogiannis-Meimarakis & Koutrika, 2023; Shi et al., 2024). Traditional approaches rely on static parsing or hand-engineered rules, leading to inaccuracies when confronted with new schemas, evolving user needs, or domain-specific language (Hong et al., 2024; Shi et al., 2024; Zhu et al., 2024). Without agentic reasoning, where AI systems can autonomously adapt to user objectives and changing data structures, Text2SQL methods often fail in dynamic settings, such as healthcare databases with frequently updated schemas or community archives with heterogeneous organizational formats (Tarbell et al., 2023). Consequently, the lack of agentic adaptability limits the practical benefits of AI-based database interactions and data retrieval (Crowe & Laux, 2023; Shi et al., 2024; Zhao et al., 2024).

1.3 Objectives and Scopes

This thesis aims to address the challenges outlined in the previous section by adopting a multifaceted approach that leverages Multimodal AI, generative models, and agentic frameworks. Specifically, it pursues the following objectives:

1.3.1 Enhancing ASD Clinical Diagnostics and Therapies Through Multimodal AI

By integrating text, speech, and visual data, Multimodal AI offers a nuanced understanding of ASD-related behaviors that surpasses traditional methods (Artsi et al., 2024; Deng et al., 2024; Rouzbahani & Karimipour, 2024; Tarbell et al., 2023; Washington & Wall, 2023). This dissertation will investigate how combining these modalities can improve diagnostic accuracy and foster more effective therapeutic strategies (Feng et al., 2024; John, 2023; Sundas et al., 2023).

1.3.2 Personalizing Learning with Gen AI for ASD Individuals

Gen AI models—particularly LLMs—can be customized to create individualized educational content that adapts to varying cognitive profiles and learning speeds (Bertacchini et al., 2023; Iannone & Giansanti, 2023; Li et al., 2024). This thesis aims to evaluate whether and how generative frameworks can reduce cognitive barriers and enhance engagement in ASD interventions (Feng et al., 2024; Hu, 2024; Mishra & Welch, 2024).

1.3.3 Reconstructing Endangered Languages Using LLMs

The critical loss of linguistic diversity can be partly mitigated by leveraging LLMs trained on fragmented historical corpora (Ginn et al., 2024; Pinhanez, 2024). Here, the research will explore how computational reconstructions of phonetics, lexicon, and syntax can revitalize endangered languages and foster intergenerational language transmission (Carta et al., 2024; Nanduri & Bonsignore, 2023; Shu et al., 2024; Spencer & Kongborrirak, 2024; Yang et al., 2024).

1.3.4 Developing Agentic AI Approaches to Text2SQL

Many Text2SQL systems remain limited by static parsing rules (Shi et al., 2024). Auto DB Agent is an agentic AI framework that autonomously adapts to novel user queries and evolving database schemas. It can facilitate democratized data access for users with varying technical expertise (Ma et al., 2024, 2024; Wang et al., 2023; Xie et al., 2024). This study investigates how such frameworks can streamline database interactions for educators, clinicians, and cultural historians alike (Lee et al., 2023; Qin et al., 2024; Tarbell et al., 2023; Wang et al., 2023).

1.4 Structure of the Thesis

To address the objectives outlined in Chapter 1, this dissertation progressively develops a conceptual and empirical foundation, ultimately converging on a unified AI ecosystem for cognitive accessibility and linguistic preservation.

1. **Chapter 2: Multimodal AI for Clinical Analysis of ASD** delves into multimodal approaches to enhance diagnostic precision and therapeutic practices for Autism Spectrum Disorder (ASD). This chapter provides a critical analysis of existing literature on how Multimodal AI can capture behavioral subtleties often missed by conventional methods.
2. **Chapter 3: Gen AI Approach for Autism Therapies** builds upon the multimodal framework by examining generative models, including LLMs, used to create personalized and adaptive therapeutic materials for individuals with ASD. This chapter underscores the role that AI-driven content plays in fostering better communication skills and social-emotional growth.
3. **Chapter 4: Revitalization Framework of Linguistic Heritage (RFLH)** shifts focus from cognitive accessibility to cultural preservation, illustrating how AI can reconstruct and revitalize endangered languages through phonetic, syntactic, and semantic analysis. By proposing a systematic framework, RFLH, this chapter highlights AI’s potential to empower communities in reclaiming at-risk linguistic identities.
4. **Chapter 5: Data Challenges** discusses the practical hurdles involved in gathering and managing large-scale, multimodal datasets across healthcare, education, and cultural archives. Topics include infrastructural limitations, governance constraints, and the need for more inclusive AI tools, laying the groundwork for why agentic solutions are essential.
5. **Chapter 6: Agentic AI Approach to Text2SQL Generation** introduces the Auto DB Agent—an agentic AI framework—designed to automate database queries using natural language. This chapter details how Data Definition Language (DDL) and retrieval-augmented generation (RAG) techniques adapt to evolving schemas, clarify ambiguous user

inputs, and democratize data retrieval for clinicians, educators, and language preservationists alike.

Chapter 2

Multimodal AI for clinical analysis of Autism Spectrum Disorder (ASD)

2.1 Introduction

Traditional diagnostic methods for Autism Spectrum Disorder (ASD), often rely on subjective assessments and time-consuming evaluations and face limitations in accuracy and efficiency. As the understanding of ASD grows, there is a pressing need to explore innovative approaches.

Applied multimodal artificial intelligence (AI) stands at the forefront of this transformation. Technologies like Magnetic Resonance Imaging (MRI), combining neuroimaging modalities and clinical data, are emerging as essential tools in the diagnostic process. One study shows that integration of multimodalities promises a more systematic approach to identifying ASD-related speech disorders, further emphasizing the need for innovative solutions in clinical analysis (Abdulla et al., 2022) (Bondarenko et al., 2025).

In this chapter, we will delve into clinical analysis using Multimodal AI to enhance clinical data and behavioral assessments, leveraging advanced AI techniques to recognize patterns and improve patient outcomes.

2.1.1 Definition of Autism Spectrum Disorder ASD

ASD is a neurodevelopmental disorder that significantly impacts the social and communication skills of individuals. As defined by the American Psychiatric Association, ASD encompasses challenges in social reciprocity, nonverbal communication, and relationship management, often emerging in early childhood. These characteristics highlight the complexity of the disorder, varying widely among individuals—some may exhibit marked social deficits, while others may demonstrate intense fixation on specific interests.

Understanding ASD not only requires clinical observations but also insights gained from innovative technologies. Recent advancements in applied Multimodal AI have the potential to enhance clinical analysis by integrating various data types, improving diagnostic accuracy, and treatment efficacy.

2.1.2 Importance of clinical analysis in ASD

The clinical analysis of ASD is significantly important as it facilitates early diagnosis and intervention. Effective clinical analysis of ASD encompasses various detection methods (Abdulla et al., 2022), for example, MRI analysis to assess brain structure and function, behavioral observations to identify social and communication patterns, hearing and vision screening to rule out sensory deficits that may affect behavior, genetic testing to explore potential hereditary factors, and cognitive assessment to evaluate cognitive abilities and challenges.

A comprehensive assessment typically involves a multidisciplinary team comprising developmental pediatricians, child psychiatrists, psychologists, speech therapists, and occupational therapists. This collaborative approach ensures a thorough evaluation and tailored intervention strategies to address the unique needs of each child. However, traditional diagnostic processes are labor-intensive and time-consuming, underscoring the necessity for advancements in automated diagnostic systems.

2.2 Understanding Multimodal AI

The recent advancement of Multimodal AI technologies signifies a transformative approach to understanding and diagnosing ASD. By synthesizing and analyzing data from various sources, such as neuroimaging, genetic information, and behavioral assessments, these data offer a more comprehensive analysis than traditional methods.

For instance, Machine Learning (ML) techniques have been used to deconstruct the neurobiological heterogeneity of ASD, facilitating the identification of distinct subtypes (Antoniades et al., 2024). Integrating ML with both functional and structural MRI techniques has become critical in identifying distinctive biomarkers for ASD, allowing for nuanced insights into the disorders (Abdulla et al., 2022).

As healthcare providers increasingly incorporate these technologies, patients benefit from applications designed to interpret diverse inputs—from text and speech to visual cues—thereby increasing the effectiveness of clinical assessments and treatments (Alamoodi et al., 2023).

2.2.1 Definition and components of Multimodal AI

Multimodal AI refers to systems that integrate and process data from multiple modalities, such as visual, auditory, and textual inputs, to deliver more comprehensive insights and analyses. This approach is particularly relevant in clinical settings where individual symptoms of ASD must be assessed for tailored interventions.

By employing techniques from ML and Deep Learning (DL), Multimodal AI systems can process and synthesize information from sources like neuroimaging and behavioral assessments, facilitating more accurate diagnoses. For instance, technologies utilizing both functional and structural neuroimaging modalities, such as fMRI and sMRI, can significantly enhance diagnostic accuracy by capturing different aspects of brain activity associated with ASD (Abdulla et al., 2022).

Furthermore, it is crucial to understand Intrapersonal Synchrony (IaPS) —the coordination of various communicative modalities within individuals—in early ASD diagnosis. Multimodal approach offers deeper insights into the unique challenges faced by those with ASD (Bloch et al., 2023).

2.2.2 Types of data used in Multimodal AI

Multimodal systems integrate text, audio, and visual data, allowing for a nuanced understanding of ASD manifestations. Textual data, primarily from clinical notes and behavioral assessments, offers context for individual cases. Audio inputs, such as vocal patterns, contribute to emotional recognition and communication challenges. Visual data, derived from neuroimaging techniques like fMRI and EEG, helps map neurological differences associated with ASD.

This approach enables a more comprehensive understanding of complex manifestations of ASD, potentially leading to earlier and more accurate diagnoses and personalized treatment. ultimately driving better outcomes in the treatment of ASD.

Table 1

Common Data Types in Multimodal AI for ASD Analysis

Data Type	Description	Example Application
Text	Clinical notes, patient reports, diagnostic criteria	Natural language processing of medical records
Audio	Speech samples, vocal patterns, prosody	Analysis of speech characteristics in ASD
Visual	Brain scans (MRI, fMRI), facial expressions, eye-tracking data	Neural network analysis of brain imaging
Physiological	Heart rate, skin conductance, EEG readings	Monitoring stress responses in ASD patients
Behavioral	Movement patterns, social interactions, repetitive behaviors	Computer vision analysis of stereotypic movements

2.2.3 Multimodal vs. unimodal methods in clinical analysis

Multimodal approaches in AI yield significant advantages over unimodal methods, particularly in the context of clinical analysis (Arco et al., 2023). The comprehensive data integration facilitates intrapersonal synchrony, enabling healthcare providers to identify nuanced behavioral patterns of individuals with ASD (Bloch et al., 2023).

A recent study assessed 97 cases in clinical analysis, comparing unimodal and multimodal algorithms for clinical decision-making across various medical specialties, dataset sizes, and data modalities. The findings revealed that multimodal approaches outperformed unimodal ones in 91% of the cases (Benani et al., 2025).

2.2.4 Current trends in AI technology relevant to healthcare

One of the most exciting trends we are seeing is the integration of ML and data fusion techniques. This shift is particularly beneficial for analyzing complex conditions like ASD. By combining various data sources, such as functional neuroimaging and clinical evaluations, healthcare professionals can create more comprehensive diagnostic frameworks that lead to better clinical outcomes.

Furthermore, there's a strong emphasis in the European Union on developing human-centered and trustworthy AI. This aligns well with the growing demand for transparency in healthcare applications. Recent studies on trustworthiness and bias reduction in AI systems underscore the need for explainable AI (Alamoodi et al., 2023). This focus is crucial for establishing reliable decision-making processes in clinical environments (Bigio et al., 2022), ultimately paving the way for more effective and personalized therapeutic practices.

2.3 Applications of Multimodal AI in ASD Diagnosis

Multimodal AI applications harness data from various sources, including neuroimaging techniques such as functional and structural magnetic resonance imaging (MRI), alongside behavioral assessments and demographic information, to enhance diagnostic accuracy. The integration of AI technologies in detection frameworks reduces the labor-intensive manual analyses, allowing specialists to make informed decisions more efficiently (Abdulla et al., 2022). Furthermore, by utilizing these advanced algorithms, clinicians can better understand individual profiles of ASD (Gorriz Sáez et al., 2022). The synergy between Multimodal AI and clinical practice is thus paramount in fostering effective ASD diagnosis.

2.3.1 Integration of behavioral analysis and physiological data

Combining behavioral analysis with physiological data enables us to utilize observable behaviors alongside biometric metrics, creating a more holistic profile of the individual. For instance, leveraging ML algorithms to analyze facial expressions, body language, and physiological responses like heart rate variability adds depth to traditional behavioral observations. Using ML algorithms alongside neuroimaging allows for the analysis of complex neural patterns and correlates them with behavioral data, leading to more precise evaluations (Elghaish et al., 2024). Furthermore, innovations in data collection methods, such as eye tracking and EEG, provide valuable insights into the emotional and cognitive processes that contribute to behavioral expressions in ASD (Bondarenko et al., 2025). These comprehensive approaches help us gain a deeper understanding of ASD, enabling tailored interventions that address both the behaviors and the underlying physiological aspects.

2.3.2 Use of Natural Language Processing in patient assessments

Natural Language Processing (NLP) plays a critical role in analyzing how patients communicate, helping to uncover underlying behavioral patterns and cognitive processes that traditional diagnostic methods might miss. By processing large amounts of linguistic data, NLP enhances the early detection of ASD, enabling practitioners to identify key indicators associated with the condition.

Recent advancements in LLMs have significantly advanced in text-based analysis. Research shows that combining LLMs with techniques like eye tracking and behavioral coding can significantly improve diagnostic accuracy and treatment planning (Elghaish et al., 2024). However, we still face challenges in interpreting subtle behaviors, as current technologies often struggle to capture these nuances (Bartlett et al., 2020).

2.3.3 Case studies showcasing successful AI applications

Multimodal AI applications in the clinical analysis of ASD have yielded promising outcomes. By harnessing the power of AI, healthcare providers can achieve enhanced diagnostic accuracy, create tailored treatment plans, and improve patient monitoring and intervention strategies.

Here are a few successful AI applications in ASD management:
By employing advanced image processing techniques in medical diagnostics, DeepScan AI enables faster and more accurate diagnoses of ASD. This technology has the potential to identify subtle neurological markers that may be overlooked in standard evaluations. (Rêgo et al., 2024)

Predictive Health Analytics leverages big data to anticipate developmental outcomes and associated risks. By facilitating personalized early interventions, it enhances long-term care strategies, helps prevent comorbidities, and improves patient adaptability and overall health outcomes. (Rêgo et al., 2024)

RoboTherapist 360 utilizes interactive robots to deliver consistent therapeutic activities. By facilitating structured therapy sessions, it enhances the development of social and communication skills, making therapeutic interactions more accessible and effective for users. (Rêgo et al., 2024)

VitaMon AI offers continuous, real-time monitoring of vital signs and behavioral patterns. It ensures constant vigilance without requiring direct human supervision, promptly alerting caregivers to potential health crises or behavioral concerns that may require immediate intervention. (Rêgo et al., 2024)

CliniHelp Decision AI decision support system helps clinicians in selecting optimal treatment plans. By facilitating rapid, evidence-based decision-making, it minimizes treatment errors and fosters greater patient trust in medical interventions. (Rêgo et al., 2024)

TalkEase Bot is specifically designed for therapeutic interaction and support. It provides continuous emotional support and effective anxiety management, teaches valuable coping mechanisms, and interactively enhances life skills training. (Rêgo et al., 2024)

2.4 Challenges faced in implementing AI for diagnosis

As the integration of Applied Multimodal AI in the clinical analysis of ASD grows, data privacy and ethical considerations becomes increasingly relevant. Using AI technologies requires collecting and analyzing sensitive personal data, which raises concerns about bias and the risk of misuse. Ethical frameworks must guide the development of these technologies to ensure both effectiveness and fairness. Given the high prevalence of ASD among children, robust data protection measures are crucial to safeguard personal information, ensuring AI applications in healthcare are trustworthy.

One major issue is the gap between lab research and real-world use. While AI diagnostic models may perform well in controlled settings, they often struggle in everyday clinical environments due to differences in data quality and availability (Bron et al., 2023). Another challenge is the need for high-quality, multimodal data. Combining various data sources requires advanced algorithms and careful validation processes (Bondarenko et al., 2025). Additionally, many clinicians are hesitant to adopt AI tools because they are not familiar with them and may distrust machine-generated assessments.

To successfully integrate AI diagnostics into clinical practice, these challenges need to be addressed. This will help ensure that technological advancements genuinely improve patient care.

Table 2

Challenges in AI Implementation for ASD Diagnosis

Challenge	Description	Impact	Potential Solution
Data Quality	Inconsistent or incomplete patient data	Reduced accuracy of AI models	Standardized data collection protocols
Algorithmic Bias	AI models may reflect societal biases	Misdiagnosis in underrepresented groups	Diverse training datasets and bias audits
Interpretability	Difficulty explaining AI decision-making	Reduced trust from clinicians	Explainable AI techniques
Integration	Incorporating AI into existing clinical workflows	Resistance from healthcare professionals	User-friendly interfaces and training programs
Regulatory Approval	Meeting stringent healthcare regulations	Delayed implementation of AI tools	Collaboration with regulatory bodies

2.5 Conclusion

The integration of Multimodal AI into the clinical analysis of ASD marks a significant shift towards enhanced diagnostic precision and improved therapeutic interventions. By utilizing advanced imaging techniques such as MRI and behavioral assessment data with machine learning and deep learning methodologies, healthcare professionals can streamline the traditionally labor-intensive and complex process of diagnosing ASD.

The combination of AI technologies and therapeutic techniques improves diagnostic accuracy and helps us better understand language development and behavior interventions in children with ASD. By fostering collaboration across various domains, we can create a more supportive and effective framework for understanding and addressing the complexities of ASD.

Chapter 3

Gen AI Approach for Autism Therapies

3.1 Introduction

Research indicates that assistive AI can enhance social and collaborative abilities among children with Autism Spectrum Disorder (ASD). Unlike traditional learning platforms, these adaptive tools cater to the unique characteristics of each user, creating personalized experiences that resonate on an individual level.

Moreover, many of these tools incorporate shared concepts that reinforce their tailored nature. Recent advancements in LLMs also enable conversational AI agents to bridge communication gaps and cultivate emotional connections (Gutiérrez et al., 2022).

In this chapter, we will delve into the advancements and their potential to redefine autism therapies through the application of Gen AI. By integrating AI technology with therapeutic practices, we can unlock new possibilities for growth and learning in the ASD community.

3.1.1 Overview of traditional autism therapies

Traditional autism therapies primarily rely on hands-on techniques that integrate behavioral modifications with educational support, each tailored to meet the unique needs of individuals on the autism spectrum. One widely used method is Applied Behavior Analysis (ABA), which aims to enhance communication, social interaction, and daily living skills, ultimately helping individuals feel more connected in their everyday lives.

The ABA process involves extensive data collection and regular assessments to adjust intervention plans, which is not always a predictable process. In some cases, medications are introduced to alleviate additional symptoms. Although symptom-focused interventions have provided significant benefits to many individuals, they frequently fall short in addressing deeper underlying issues. These include individual variability, social skills deficits, co-occurring conditions, and communication difficulties.

Recent advancements in genetic research are paving the way for treatments that could be more precise and personalized (Chen et al., 2022). Additionally, the increasing use of AI and robotic technologies in therapy settings suggests a promising future where engagement and therapeutic outcomes may reach unprecedented levels (Albo-Canals et al., 2019).

3.2 Understanding Gen AI

The rise of Gen AI signifies a groundbreaking change in various domains, particularly in therapeutic approaches for ASD. By utilizing sophisticated machine learning algorithms, Gen AI can generate tailored content and interactive settings that address the specific needs of individuals with ASD. These innovative approaches are often effective in enhancing essential skills such as teamwork and social interactions, facilitating smoother integration into everyday life (Cañete et al., 2022).

Moreover, the investigation of Brain Machine Interface (BMI) technologies further enriches this field, providing new methods to interpret and stimulate brain activity, potentially enhancing therapeutic outcomes for individuals confronted with severe autism-related challenges (Abdi et al., 2022).

Understanding Gen AI opens new paths for therapeutic interventions and highlights the importance of integrating modern technologies. This integration is crucial for enhancing communication and social skills in children with ASD.

3.2.1 Introduction to Gen AI in therapy

Research indicates that many autistic individuals prefer engaging with an LLM for advice on workplace social dynamics over consulting a human. This preference suggests that interactions with AI can be perceived as less judgmental, fostering a more open dialogue (Begel et al., 2024).

Moreover, Gen AI can be integrated with various modalities such as Dance Movement Therapy (DMT), promoting creative expression and encouraging inclusive practices. This combination appears to cultivate environments where emotions and interpersonal connections can shine through more easily (Quintar A et al., 2024).

Collectively, these advancements pave the way for personalized treatment strategies for individuals on the autism spectrum, establishing pathways that are both innovative and seamlessly integrated into therapeutic practices.

3.2.2 Gen AI technology

Gen AI operates by training machines to create new content based on vast amounts of existing data. In autism therapies, this new technology might upend the usual methods, offering interventions that that adapt to the unique needs of individuals. AI excels at identifying behavioral patterns and personal characteristics in autistic individuals, enabling the development of treatment plans that feel almost custom-made.

Additionally, exploring emerging treatments associated with Klotho proteins, which play a crucial role in brain health, using advanced Gen AI algorithms opens new avenues for refining these therapies (Wang Y et al., 2024). This underscores the promise of Gen AI in addressing complex neurodevelopmental challenges (Chen et al., 2020).

By integrating and analyzing diverse data sources—such as behavioral observations, speech patterns, and physiological responses—in real-time, these models can identify subtle behavioral indicators of ASD. This comprehensive approach allows for a more nuanced understanding of each child's unique profile, ultimately facilitating quicker access to necessary support and tailored interventions.

For instance, the integration of Child-Robot Interaction (CRI) concepts into robotic systems allows these technologies to identify behaviors indicative of ASD. This capability facilitates early assessments and leads to more personalized treatment options for affected children (Duque et al., 2019). Furthermore, deep learning methods have advanced healthcare data analysis, providing insights that can predict a child's developmental trajectory and refine treatment plans accordingly (Arco et al., 2023).

3.3 Enhancing Communication Skills

Recently, educators have begun to integrate innovative technologies to facilitate more natural communication for individuals with autism. Conversational AIs are increasingly prominent in support sessions, specifically designed to address the unique communication challenges associated with ASD. These tools are seamlessly incorporated into social interactions, providing practical assistance. Research indicates that such technologies engage users effectively and enhance their emotional awareness, which is crucial for fostering meaningful connections (Albo-Canals et al., 2019).

Moreover, studies highlight the efficacy of unconventional methods, such as using emojis as a shorthand for expressing feelings. This approach helps in interpreting emotional cues and navigating social interactions, providing additional support (O'Brian et al., 2020).

3.3.1 Benefits of using Gen AI in educational settings

In educational settings, where traditional classroom methods frequently fall short, AI offers personalized support that addresses gaps in understanding. It provides customized and interactive learning experiences tailored to the diverse needs of students facing various educational challenges (Peterkin-Rawls et al., 2024). By leveraging Gen AI, therapeutic interventions may become more effective and accessible, ultimately enhancing the learning and development process for many.

Rather than relying on methods that heavily depend on human judgment, Gen AI such as LLMs provides an innovative approach to enhancing communication skills that many individuals struggle with in face-to-face interactions. Research indicates that autistic adults often prefer digital communication over direct human interaction, making LLMs an ideal platform for safe social advice and practice opportunities (Begel et al., 2024).

3.3.2 AI-driven tools for speech and language development

The approach to conducting therapy sessions for children with ASD is being revolutionized by AI-powered tools for speech and language therapy. By utilizing reasoning agents, these innovative systems tailor each session to align with the individual learning styles of children, enhancing engagement in the therapeutic process. Research indicates that AI-based robot platforms can create interactive, pressure-free environments where children with speech delays can comfortably practice communication skills (Hanapiah et al., 2024).

At the same time, incorporating neuro-ethics into the clinical use of AI raises critical questions about how we make sure these tools respect the autonomy and overall well-being of children. This highlights the necessity for well-defined ethical guidelines to navigate the complexities associated with these technologies (Marder E et al., 2008).

3.3.3 Personalized learning experiences through AI

Today, educational tools increasingly incorporate advanced machine learning techniques to tailor lessons to unique needs of each student. Chat-based assistants like OpenAI ChatGPT and QAI offer immediate, personalized feedback on essential skills such as emotional regulation and social interaction (Dave et al., 2023). The level of personalization not only boosts student engagement with the material but also significantly enhances the retention of learned concepts.

Certain systems track eye movements and analyze behavior patterns in real-time, offering insights into student interactions with content. This data enables teachers to adjust their teaching strategies dynamically, resulting in a more effective learning experience (Elghaish et al., 2024). The combination of technology and personalized instruction creates an inclusive and supportive classroom environment, allowing students with ASD to excel both academically and socially.

3.3.4 Case studies showcasing improved communication outcomes

Recent research shows Gen AI has the potential to significantly enhance communication for individuals on the autism spectrum. By integrating LLMs into movement therapy as an alternative to traditional talk therapy, it offers personalized support and facilitates cognitive reframing. This innovative method allows individuals to express themselves in immersive environments, fostering a sense of belonging that older therapeutic approaches often overlook (Quintar A et al., 2024).

One study highlighted the effectiveness of combining AI with traditional art materials to explore story-making as a therapeutic tool. This combination resulted in deeper emotional sharing among families and encouraged more natural conversations at home (An et al., 2024). These examples illustrate that the fusion of creative art and technology can unlock unexpected avenues for improved communication in autism therapies.

3.4 Social Skills Development

Individuals with autism often face challenges in communication and social interactions, prompting the exploration of innovative approaches to foster connections. Recent studies indicate that AI tools, which provide immediate and personalized feedback, can significantly help children in understanding and responding to social cues in real-time (Acharya et al., 2023).

Additionally, the incorporation of social robots into therapy sessions offers children a unique opportunity to practice and refine their social skills in a relaxed and controlled environment (Albo-Canals et al., 2019). This setting encourages experimentation and learning without the pressure of real-world consequences.

These technological advancements go beyond merely practicing isolated skills; they also enhance overall learning outcomes and meet the increasing demand for evidence-based interventions in autism care.

3.4.1 Virtual reality environments powered by AI for social interaction

Innovative approaches in autism therapy also emerge from the integration of Virtual Reality (VR) and AI. These immersive digital environments allow individuals to engage in simulated social scenarios tailored to their specific needs. It enables them to practice conversation and connection without the pressures of real-world interactions. Gen AI analyzes user reactions in real-time and dynamically adjusts the experience, providing subtle prompts that encourage the development of positive social habits.

Research shows that this type of interactive, adaptive experience not only enhances learning but also alleviates anxiety associated with socializing (Hutson et al., 2024). Furthermore, there is significant potential for wearable devices to complement VR by adjusting sensory inputs to accommodate various sensitivities. The additional layer of customization creates a more comprehensive therapeutic approach for neurodivergent individuals, enhancing their overall experience and effectiveness in social skills development (Hutson et al., 2024).

3.4.2 AI simulations for practicing social scenarios

AI-driven simulations designed for practicing social interactions are increasingly adopted to augment autism therapies. These tools immerse users in realistic, controlled environments where people on the autism spectrum can explore different social cues and responses. Frequently, the systems adapt in real-time, observing how individual acts and modifying the experience to align with their individual style (Bresó Guardado et al., 2016).

This personalized adaptation generally enhances engagement and effectiveness, as even minor adjustments can lead to significant improvements. As AI technology continues to advance, it increasingly incorporates knowledge from neuroscience and machine learning, creating simulations that reflect more complex social interactions (Bologna et al., 2020).

3.4.3 Impact of AI on peer relationships and social integration

AI-driven interactive applications actively engage users in innovative ways that often elude conventional approaches. These new approaches not only spark conversations but also create opportunities to deeper emotional expression and learning. For instance, (Silva et al., 2023) demonstrates that incorporating AI into music therapy can facilitate emotional sharing and self-expression within a framework that promotes personal growth.

However, as therapeutic AI become increasingly prevalent, questions arise regarding their true impact on everyday social interactions. It is critical to examine the ethical and societal implications of AI-assisted therapy, to ensure they genuinely foster stronger peer relationships among individuals with autism. (Albo-Canals et al., 2019)

3.5 Conclusion

Technology is revolutionizing autism treatment, presenting opportunities that could significantly alter therapeutic approaches and warrant careful consideration. The technology uses advanced machine learning to analyze individual behavior patterns, customize therapies and introduces innovative ways to foster connections, particularly in digital environments like the Metaverse. Research suggests that these virtual spaces can provide a more relaxed atmosphere for individuals with autism to practice social skills without the typical pressures of real-life interactions (Hocaoğlu et al., 2024). However, challenges remain, such as ensuring inclusive access for all users and the necessity for more comprehensive research to establish long-term benefits.

3.5.1 Summary of the potential of Gen AI in autism therapies

Gen AI has unlocked exciting new possibilities that address the unique needs of individuals in autism therapies. It facilitates the creation of customized environments where social interactions can occur more naturally. For instance, consider integrating the AI into DMT, a new method may interactively bridges social gaps and enhances motor skills for individuals with ASD (Quintar A et al., 2024).

These advanced AI tools often adapt in real-time, modifying therapeutic content based on users immediate responses, which can significantly enhance the effectiveness of treatment. By prioritizing user-friendly designs, Gen AI fosters a more flexible and inclusive therapeutic framework that can help alleviate some of the everyday challenges faced by autistic individuals (Chen et al., 2020).

3.5.2 Future directions for research and implementation

AI and robotics are increasingly finding their place in autism. For example, robots like Kaspar and Nao may facilitate social interactions and enhance learning for autistic children. This development necessitates further studies of how technologies influence their social and cognitive skills over time (Albo-Canals et al., 2019).

The concept of the Metaverse introduces an exciting opportunity to create immersive environments that can alleviate anxiety and enhance social skills, without the complications of real-world interactions (Hocaoğlu et al., 2024). However, alongside this promising potential, ethical considerations are emerging, highlighting the need for practical research.

Collaborating with technologists, therapists, and ethicists is essential to address these challenges effectively. This multidisciplinary approach will help ensure that advancements in treatment are not only effective and safe but also accessible to all individuals on the autism spectrum.

3.5.3 Final thoughts on the importance of innovation in autism treatment

Autism remains a complex challenge that many face, making the pursuit of innovative and creative solutions more crucial than ever. AI is playing a pivotal role by enhancing our understanding of brain function, combined with advanced technology like MRI, facilitating the identification of patterns that might otherwise go unnoticed. These AI tools not only accelerate the detection process but also customize treatments to better meet the unique needs of individuals.

Researchers worldwide are discussing how such technologies are paving the way for new insights into autism (Hughes et al., 2024), representing a collaborative effort in rethinking our approaches. Moreover, the application of AI in developing detection systems addresses challenges of early diagnosing ASD (Abdulla et al., 2022). Embracing and implementing new ideas in autism treatment is essential for achieving better.

Chapter 4

Revitalization Framework of Linguistic Heritage (RFLH) using AI

4.1 Introduction

In the context of global cultural diversity and identity, many marginalized languages face the risk of extinction due to sociopolitical and technological changes. The preservation of lost linguistic heritage has become increasingly significant (Bondarchuk V, 2024). Historical linguistics shows that language is more than just a way to communicate. It also carries culture, traditions, and community bonds. This underscores the importance of revitalizing languages that hold significant cultural value (Lian Y et al., 2024).

Efforts to restore languages are often hindered by the lack of substantial written or recorded materials, making it difficult to recover these lost heritages (Jopling M et al., 2024). The main question is how LLMs, like GPT-4, DeepSeek V3, and Llama 3, can effectively address this gap and replicate the linguistic structures of endangered languages (Gregory N Bratman et al., 2024).

In this dissertation, we will investigate the potential applications of LLMs in generating coherent linguistic outputs for underrepresented languages, restoring their phonetic, syntactic, and semantic characteristics (Iona AEșcu et al., 2024). It includes creating a comprehensive dataset that combines historical linguistic records with modern social contexts and evaluating how well LLMs generate relevant language outputs (Guerrero-Moreno MA et al., 2024).

We hope to provide the Revitalization Framework of Linguistic Heritage (RFLH), a framework for integrating linguistic diversity into various fields, ensuring better inclusion for minority communities (Grigar D et al., 2024). By decoding the hidden narratives through the lens of modern technology, we promote a deeper appreciation of linguistic heritage and its vital role in shaping cultural identity in the interconnected world today (Xu Y et al., 2024a), (Montero FR et al., 2024), (Nassiri K et al., 2024).

4.2 Overview

4.2.1 Definition of Linguistic Heritage

Linguistic heritage refers to the languages and dialects that are passed down through generations within a community, reflecting its culture, history, and identity. This concept goes beyond vocabulary and grammar. It includes the unique cultural expressions and social knowledge tied to each language, facilitating communication among diverse communities. Understanding linguistic heritage becomes vital in a globalized world where many languages and cultures face extinction.

Recent technological advancements, particularly in Multimodal LLMs, provide new ways to preserve and revitalize endangered languages, connecting historical linguistic heritage with modern digital environments (Chen et al., 2024a). Research in territorial intelligence shows that using Multimodal LLMs can improve our understanding and efforts to restore linguistic heritage, helping ensure that these invaluable languages do not disappear (Girardot et al., 2007).

4.2.2 Importance of Preserving Linguistic Diversity

Preserving linguistic diversity is essential for protecting the cultural identities and knowledge systems they carry. Each language reflects unique worldviews, histories, and traditions, highlighting that losing a language means losing a vital part of our shared human heritage.

As globalization accelerates, more than 2,500 languages are at risk of extinction, according to The United Nations Educational, Scientific and Cultural Organization (UNESCO), leading to a significant loss in our collective appreciation of cultural diversity. Protecting endangered languages is not just about words; it's about safeguarding entire knowledge systems, cultural identities, and ways of understanding the world.

The complexities of language preservation require a careful approach, recognizing that not all languages can be restored for functional use. In some cases, focusing on archiving these languages may be more practical and sustainable, ensuring that linguistic data is preserved for future generations and supporting cultural continuity (Are et al., 2015).

4.2.3 Roles of LLMs in Linguistic Revitalization

LLMs have significantly changed the field of computational linguistics by enabling advanced tasks like text generation and machine translation. These models are designed to understand and produce human-like language, making them essential tools for linguistic research and the preservation of cultural heritage.

Using advanced algorithms and large datasets, LLMs can analyze patterns in ancient texts, reconstruct lost linguistic heritages, and document endangered languages. This is especially important as experts struggle to decipher lost languages, often limited by a lack of access to linguistic knowledge or archival materials (Androutsopoulos et al., 2023).

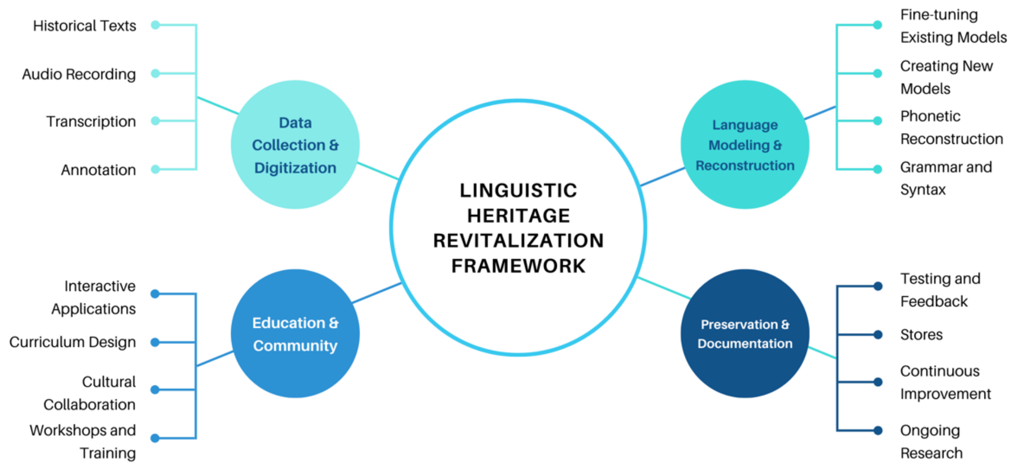
Additionally, LLMs help create multilingual metadata records, improving access to cultural artifacts and strengthening the connection between digital archives and their communities (Barczyk et al., 2015). Therefore, LLMs play a vital role in bridging technology and the humanities, facilitating the revitalization of diverse linguistic heritages.

4.3 Revitalization Framework for Linguistic Heritage

Revitalizing extinct languages requires a comprehensive and systematic approach that seamlessly integrates technology, linguistics, and cultural preservation. To achieve this, we propose the Revitalization Framework of Linguistic Heritage (RFLH), which is specifically designed to unify diverse disciplines and methodologies, ensuring that revitalization efforts are both effective and sustainable.

Figure 1

Revitalization Framework of Linguistic Heritage (RFLH)



4.3.1 Data Collection and Digitization

At the beginning stage of linguistic heritage revitalization, effective data collection and digitization are crucial for preserving and promoting endangered or extinct languages. This process involves several key activities that ensure comprehensive documentation and accessibility of linguistic resources.

4.3.1.1 Data Collection

Historical Texts: The first step in data collection is to gather all available documentation related to the extinct language. This includes manuscripts, books, and inscriptions that provide insights into the language structure, usage, and cultural significance. These texts serve as primary sources that can inform linguistic research and revitalization efforts. (Olko & Sallabank, 2021)

Audio Recordings: If there are any recordings of native speakers, these should also be collected. Such audio data is invaluable as it captures the phonetic and grammatical nuances of the language, which may not be fully represented in written texts. Linguistic studies that include these recordings can further enhance the understanding of the characteristics of languages. (Austin, P. K., 2021)

Community Input: Engaging with communities that have cultural ties to the language is another vital aspect of data collection. By gathering oral histories and insights from community members, researchers can uncover rich narratives and contextual information that are essential for a holistic understanding of the language. This engagement also helps to foster a sense of ownership and collaboration among community members in the revitalization efforts. (Hinton, 2018)

Table 3

Data Collection Techniques for Endangered Languages

Technique	Description	Effectiveness	Challenges	Digital Integration
Field Recordings	Audio/video recordings of native speakers	High	Time-consuming, requires travel	Can be processed by AI for analysis
Text Digitization	Converting written materials to digital format	Medium	Limited availability of written sources	Easily integrated with NLP models
Crowdsourcing	Collecting data from community members online	Medium	Quality control, engagement	Can feed directly into machine learning models
Archival Research	Studying historical documents and recordings	Medium	Limited to available archives	Can be digitized for AI analysis
Collaborative Documentation	Working with native speakers to document language	High	Requires skilled linguists	Can inform AI language models

4.3.1.2 Data Digitization

Once data has been collected, the next phase is digitization. This process involves converting physical texts and audio recordings into digital formats, making them more accessible and easier to work with.

Transcription: The transcription of physical documents and audio recordings is a fundamental step in digitization. This can be accomplished through both manual transcriptions, where skilled researchers carefully transcribe the materials, or by using speech recognition tools that aid in converting audio to text. Regardless of the method, accurate transcription is critical to maintaining the integrity of the linguistic data. (Eftekhari, 2024)

Annotation: After transcription, annotating the data with linguistic information is essential. This includes adding details about phonetics, grammar, and syntax, which can greatly facilitate the training of AI models and other linguistic analyses. Accurate annotation creates a systematic framework that enhances the usability of the data for researchers, educators, and language learners, facilitating more efficient analysis and learning. (Beck et al., 2020)

Table 4

Applications of LLMs in Endangered Language Documentation

Application	Description	Potential Impact	Challenges
Automated Transcription	Convert audio recordings to text	Accelerate documentation process	Accuracy for low-resource languages
Machine Translation	Translate between endangered and major languages	Improve accessibility of language materials	Maintaining cultural nuances
Grammar Inference	Identify grammatical patterns from limited data	Aid in creating language descriptions	Distinguishing true patterns from noise
Vocabulary Expansion	Generate potential word forms	Assist in dictionary creation	Verifying generated words with speakers
Language Reconstruction	Infer features of extinct languages	Recover aspects of lost linguistic heritage	Accuracy of reconstructions

4.3.2 Language Modeling and Reconstruction

Language modeling and reconstruction are important processes that use advanced technologies and collected data to revive languages that have been mostly forgotten. By training LLMs with collected data and using AI for phonetic and grammatical analysis, researchers can help communities reconnect with their cultural heritage through language.

4.3.2.1 Language Modeling

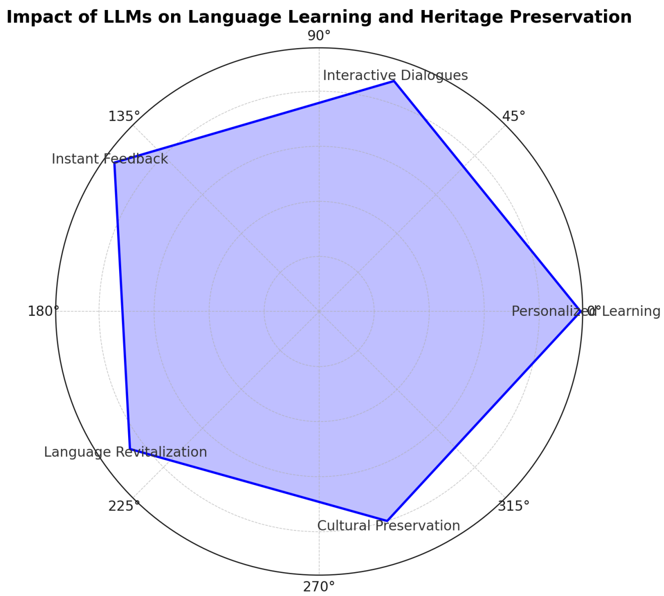
The first step in language modeling involves utilizing the collected and annotated data to train LLMs specifically designed for the extinct language.

Fine-tuning Existing Models: For languages where some resources already exist, researchers can take pre-trained transformer-based language models, like GPT-4, DeepSeek V3, and Llama 3; and fine-tune them using the specific linguistic data of the extinct language. This approach allows the model to adapt and learn the nuances of the language, improving its ability to generate and understand text in that language. (Sung & Kyle, 2024)

Creating New Models: In cases where there is very little data available, researchers may need to develop new foundation models from scratch, using reinforcement learning and in-context learning techniques. These models are designed to learn from the limited resources at hand, ensuring that even languages with scant documentation can be represented in a digital format. (Ding et al., 2024)

Figure 2

Impact of LLMs on Language Learning and Heritage Preservation (Koc, 2025)



This radar chart illustrates the multifaceted impact of LLMs on language learning and heritage preservation, rated on a scale of 0 to 100. It highlights LLMs' strengths in delivering instant feedback, language revitalization, cultural preservation (Yang et al., 2025), personalized learning experiences (Zhang et al., 2024), and facilitating interactive dialogues (Sharma et al., 2025).

4.3.2.2 Language Reconstruction

Once the models are trained, the next step is language reconstruction, which focuses on understanding and restoring the phonetic and grammatical aspects of the language.

Phonetic Reconstruction: AI models can be employed to analyze the relationship between phonetic patterns and glyph information found in the collected data. By examining these patterns, researchers can reconstruct pronunciations that might have been lost over time. This process is vital for reviving the spoken aspect of the language and ensuring that it can be accurately spoken by future generations. (Huang et al., 2024)

Grammar and Syntax: LLMs excel in generating grammatical rules and sentence structures. By drawing on patterns observed in the training data, using part-of-speech tagging, syntactic parsing, and dependency parsing techniques, these models can create frameworks for how the language should be structured. Machine learning algorithms can also be trained to classify sentences according to their grammatical correctness, significantly enhancing automated grammar checking and error detection processes. (Groenewald et al., 2024)

4.3.3 Education and Community

The development of educational tools and active community involvement are essential components of linguistic heritage revitalization. By creating interactive applications and culturally relevant curriculum materials, alongside fostering collaboration with the language community, it ensures that future generations can connect with their linguistic roots.

Interactive Applications: One of the most effective ways to teach a language is through interactive applications. These can include mobile apps and online platforms that use AI and LLMs to create engaging learning experiences. For example, chatbots can simulate conversations, allowing learners to practice their language skills in real-time. Additionally, language learning games can make the process enjoyable and motivate learners to immerse themselves in the language. (Xiao et al., 2023)

Curriculum Design: To support language learning, it's essential to create comprehensive educational materials. This includes textbooks, online resources, and multimedia content that incorporate the reconstructed language and its cultural context. By integrating cultural elements, learners can gain a deeper understanding of not just the language itself, but also the traditions and values associated with it. This approach fosters a more holistic learning experience that resonates with students. (Terrell, 2023)

Cultural Collaboration: Engaging with the speakers and descendants of the language community is vital for ensuring the revitalization efforts are culturally relevant and accurate. Their involvement helps to maintain the authenticity of the language and its usage in context. This collaboration can take many forms, including consultations during the development of educational materials or the integration of community stories and practices into the curriculum. (Murgová, 2021)

Workshops and Training: Conducting workshops is another effective way to promote language learning. These workshops can be designed for various audiences, including community members and those interested in learning the language. By using AI and big data tools during these sessions, instructors can provide personalized learning experiences, catering to different skill levels and learning styles in real-time. (Xia et al., 2024a)

Table 5

Impact of LLMs on Linguistic Research and Education

Area	Before LLMs (2020)	After LLMs (2025)	Improvement
Language Documentation	Manual transcription and analysis	Automated transcription and initial analysis	Reduction in processing time
Endangered Language Preservation	Limited resources for less-studied languages	Increased ability to process and analyze rare languages	Increase in preserved linguistic data
Historical Linguistics	Time-consuming manual comparison of language evolution	Rapid analysis of language changes over time	Faster identification of linguistic patterns
Language Learning Tools	Static textbooks and limited interactive resources	Personalized, adaptive language learning platforms	Increase in student engagement and retention

4.3.4 Preservation and Documentation

The integration of feedback and iterative processes, combined with strong preservation and documentation strategies, fosters the sustainability and ongoing enhancement of linguistic culture. Robust documentation practices provide a historical record that captures the evolution of the language and its speakers.

Testing and Feedback: One of the primary goals in linguistic revitalization is to create AI-generated outputs that reflect the nuances of the language accurately. To achieve this, it is crucial to implement systems that allow users to provide feedback on these outputs. This feedback helps identify inaccuracies and areas for improvement, ensuring that the language models are refined over time. (Li, 2023)

Continuous Improvement: Regular updates are necessary to incorporate new AI models and algorithms, and data gathered from ongoing interactions and additional research. By continuously improving the specially trained language models, researchers can better capture the dynamic nature of the language and its usage. This iterative approach enhances the quality of the linguistic outputs over time. (Wu et al., 2024)

Archiving: Creating a digital archive is essential for long-term accessibility and preservation of the reconstructed language. This archive should include not only the language itself but also all related resources, such as historical texts, audio recordings, and community contributions. A well-organized digital archive allows researchers, educators, and community members to access vital information easily, promoting ongoing engagement with the language. (Dayanand et al., 2023)

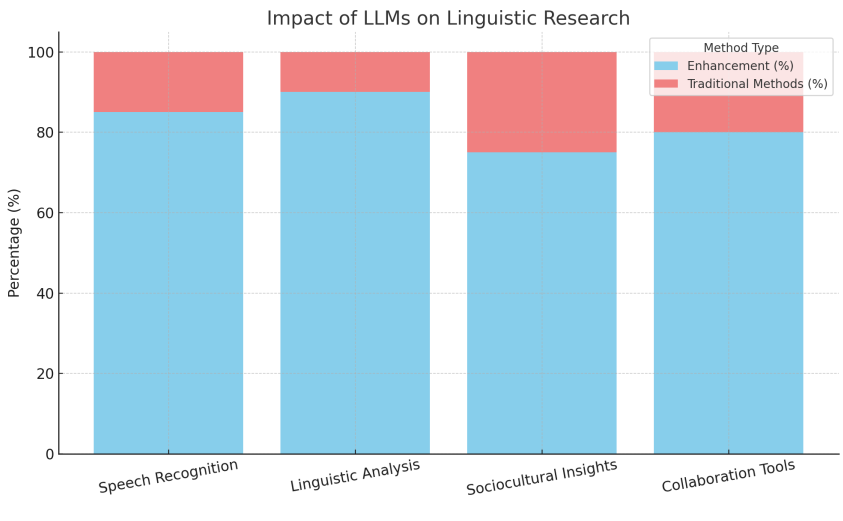
4.4 Impact of LLMs on Linguistic Research

LLMs help researchers analyze extensive text collections, enhancing our understanding of endangered and extinct languages. They also assist in creating benchmarks that guide scholars in using speech recognition systems designed for specific languages (Bălan et al., 2024). For example, the Dutch Open Speech Recognition Benchmark optimizes speech recognition in various settings.

Moreover, LLMs enable the study of different linguistic phenomena, providing insights into the sociocultural factors that affect language change. This is in line with initiatives like CAENTI, which promotes collaboration among linguists and underscores the growing importance of digital tools in research (Girardot et al., 2007).

Figure 3

Impact of LLMs on Linguistic Research



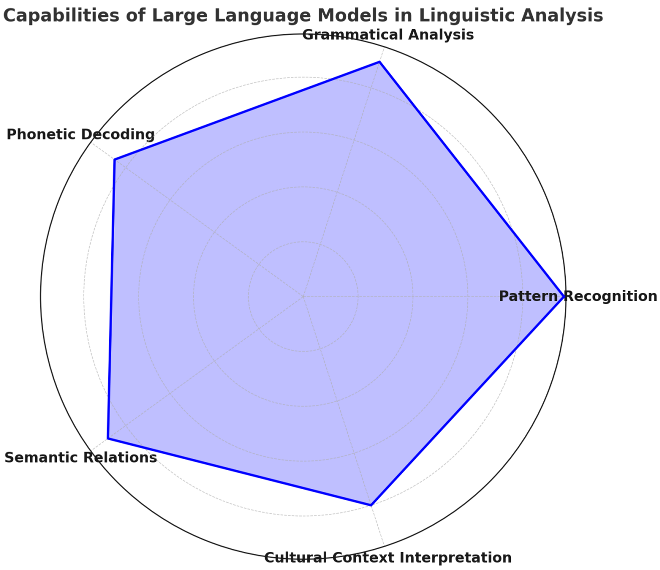
This stacked bar chart illustrates the impact of LLMs on different aspects of linguistic research, showing the percentage of enhancement versus traditional methods. It reflects the emphasis on LLMs' contributions to speech recognition, linguistic analysis, sociocultural insights, and collaborative research tools. The data highlights LLMs' significant impact across various domains of linguistic heritage restoration, with a strong influence in linguistic analysis and speech recognition (Xu Y et al., 2024b), sociocultural insights, and collaboration tools. (Ahmad, 2024) (Shirinova, 2025)(Jegan & Henrich, 2025)

Analyzing language patterns and structures is crucial for understanding and restoring lost linguistic heritage, especially with the rise of advanced technologies like LLMs. These models are skilled at recognizing and generating language patterns, allowing them to uncover complex linguistic elements that might otherwise remain hidden. For instance, by studying grammatical structures, phonetic patterns, and semantic relationships, LLMs can generate hypotheses about extinct languages that carry rich cultural histories.

Evaluations of various models, including proprietary ones like GPT-4 and Google's Gemini, emphasize the need for reliability and generalizability across different contexts, enhancing their effectiveness in this field (Chen et al., 2024a). Additionally, when examining specific linguistic structures discussed in conferences on territorial intelligence, LLMs can provide new insights into the socio-cultural factors that influenced these languages (Girardot et al., 2007).

Figure 4

Capabilities of LLMs in Linguistic Analysis

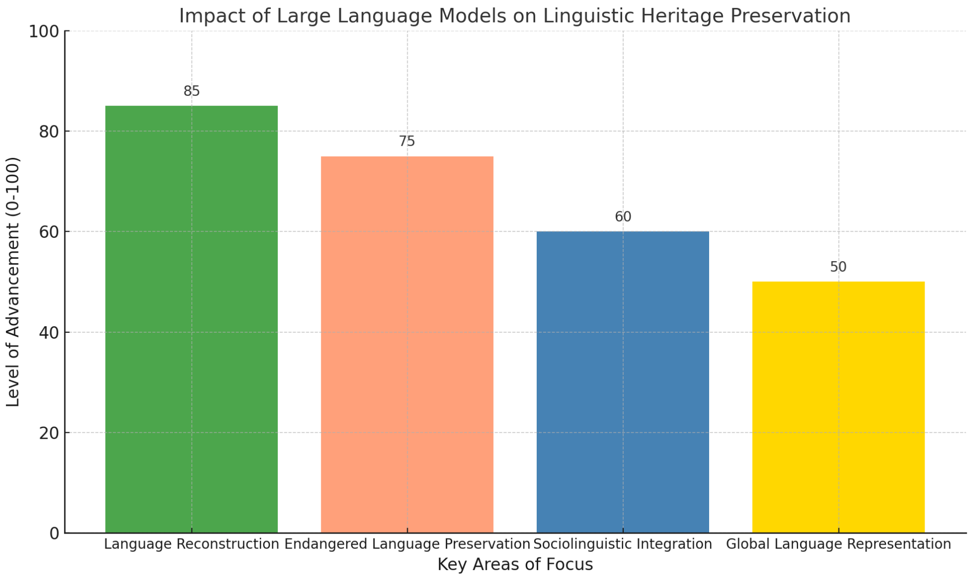


This radar chart illustrates the capabilities of LLMs in various aspects of linguistic heritage restoration. The data reflects the paragraph's emphasis on LLMs' strengths in decoding language patterns and structures. Each axis represents a key area of linguistic analysis, with values indicating the estimated effectiveness of LLMs on a scale of 0-100. The chart highlights LLMs' particular strength in pattern recognition and grammatical analysis, while also showing strong capabilities in semantic relations and phonetic decoding. The slightly lower score in cultural context interpretation acknowledges the challenges LLMs face in fully capturing socio-cultural nuances. (Lakomkin et al., 2023)(Suvarna et al., 2024)(Jones et al., 2024)

Researchers can use LLMs to reconstruct linguistic patterns that might otherwise be lost. For instance, these models can handle complex tasks like language reconstruction, offering valuable insights into endangered languages. Moreover, integrating sociolinguistic theories into the development of these models, as highlighted by Bartl et al. (2025), emphasizes the need to accurately represent different language varieties. This deeper understanding provides linguists with essential tools to preserve, document, and restore lost linguistic heritage, promoting a more inclusive view of global languages.

Figure 5

Impact of LLM on Linguistic Heritage Preservation



This stacked bar chart illustrates the impact of LLMs on various aspects of linguistic heritage preservation. The data reflects the emphasis on LLMs' capabilities in language reconstruction and preservation of endangered languages, while also highlighting the growing integration of sociolinguistic theories and the potential for improved global language representation. Each bar represents a key area of focus in computational linguistics, with values indicating the estimated current level of advancement on a scale of 0-100. The chart showcases the significant progress in language reconstruction and endangered language preservation, while also pointing to areas with potential for further development, such as sociolinguistic integration and global language representation. (Grieve et al., 2024) (Ryan et al., 2024) (Carta et al., 2024)

4.5 Conclusion

This dissertation illustrates the transformative potential of Artificial Intelligence (AI), particularly LLMs, in the revitalization of lost linguistic heritage. Through the development of the

Revitalization Framework of Linguistic Heritage (RFLH), we have established a comprehensive approach that integrates historical linguistic records with cutting-edge technologies, addressing the critical challenges faced in preserving endangered languages and dialects.

The findings demonstrate that LLMs possess remarkable capabilities in generating coherent outputs that reflect the structures of underrepresented languages. By offering insights into phonetic, syntactic, and semantic characteristics, LLMs not only advance linguistic research but also foster improved communication and understanding within communities that speak endangered languages. This research underscores the significant role LLMs can play in enhancing cultural appreciation by making linguistic information accessible to a diverse audience.

Moreover, the incorporation of sociolinguistic theories in the development of LLMs has proven essential for accurately representing various language varieties. This nuanced understanding equips linguists with the necessary tools to document, preserve, and restore lost linguistic heritage, ultimately promoting a more inclusive representation of global languages.

As we move forward, it is imperative to continue refining and expanding the RFLH, ensuring that revitalization efforts remain effective and sustainable. Engaging with linguistic communities and fostering collaborative initiatives will be vital to maintaining the authenticity and cultural relevance of revitalization projects. The insights gained from this research not only contribute to the fields of linguistics and artificial intelligence but also highlight the importance of preserving linguistic diversity as an essential component of our shared human heritage in an increasingly interconnected world.

In conclusion, the integration of LLMs in linguistic revitalization efforts represents a promising frontier in the quest to safeguard and celebrate the rich tapestry of global languages. This research not only opens new avenues for academic inquiry but also paves the way for practical applications that can enrich and empower communities, ensuring that the voices of marginalized languages resonate in the modern technological landscape.

Chapter 5

Data Challenges

5.1 Introduction

The Gen AI and multimodal models for ASD and linguistic revitalization rely on large and heterogeneous datasets that span structured datasets, audio-visual records, text corpora, and synthetic annotation. This results in data retrieval and management becoming a fundamental challenge to the scalability of AI-driven cognitive and cultural applications.

This chapter examines the data-related issues faced by clinicians, educators, and cultural workers when accessing, managing, and analyzing complex datasets. These issues affect both high-level objectives, such as automated query generation and text corpus curation, and day-to-day workflows, including logging clinical data and annotating speech metadata.

5.2 Generating and Managing Structured Data

Modern organizations in healthcare, education, and cultural preservation generate large volumes of structured data (Orji et al., 2023; Tarbell et al., 2023). This data is often stored in relational databases or extensive data warehouses. For example, in ASD therapy, clinicians may collect clinical notes, therapy session logs, patient progress metrics, and demographic information. They can use these datasets to create more personalized intervention plans for each patient. (Anderson et al., 2024; Fafalios et al., 2023; Lawson et al., 2021; Nair et al., 2021)

Similarly, those involved in linguistic preservation might gather detailed records of endangered languages. These records can include lexical databases, historical transcripts, and speaker metadata (Carta et al., 2024; Pinhanez, 2023; Smart et al., 2024). However, accessing and making sense of this information remains a major challenge. Many non-technical users—like special education teachers, community organizers, or field linguists—lack the query language skills needed to work with complex data repositories (Fafalios et al., 2023; Tarbell et al., 2023).

In the past, data extraction and analysis often required technical staff, such as database administrators or data scientists (Rogers & Crisan, 2023; Wang et al., 2022). This reliance on specialists can slow down important decisions. It can also cause delays in tasks like adjusting an ASD treatment plan or scheduling a language revitalization event. As a result, there is a growing push for natural language interfaces. These interfaces aim to help non-technical users query databases directly, which has driven research into fields such as Text2SQL and agentic AI frameworks. (Katsogiannis-Meimarakis & Koutrika, 2023; Kumar et al., 2022; Shi et al., 2024; Tian et al., 2024; Wang et al., 2022)

5.3 Unstructured and Multimodal Sources

Besides structured data, organizations also manage unstructured and multimodal content, such as text documents, images, audio recordings, and videos (Tan, 2023; John, 2023; Quamar et al., 2022; Saeed et al., 2023; Urban & Binnig, 2023). In ASD therapy, for instance, researchers might compare EEG data to written behavioral notes to find connections between neurological activity and social interactions (Eldeeb et al., 2021; Ghafghazi et al., 2021; Li et al., 2021; Liu et al., 2024; Ramesh & Assaf, 2021). In linguistic preservation, specialists may need to link audio recordings of endangered languages to written transcripts or high-resolution scans of historical documents (Carta et al., 2024; Hutson et al., 2024; McMillan-Major et al., 2022).

Due to its variety, this information demands advanced strategies for indexing and analysis. Basic keyword-based searches can work well for small or narrow data collections, but they often struggle with more context-dependent queries (Borgman et al., 2021; Lou et al., 2021; Ocaña-Fernández & Fuster-Guillén, 2021; Sharma & Jain, 2023). They also lack the ability to handle semantic details, which are key to extracting meaningful insights. This shortfall becomes clear in situations like searching for EEG findings in ASD studies or finding archival recordings for specific ceremonial chants. Traditional search tools often fail to detect linguistic nuances or match multiple media types effectively. (Almasoud et al., 2022; Dunsin et al., 2024; Hollenstein et al., 2021; Lee et al., 2022; Ribeiro & Filho, 2023)

5.4 Organizational and Infrastructural Constraints

Another challenge comes from organizational and infrastructural limitations. Many healthcare providers or cultural institutions do not have the specialized staff or funding needed for sophisticated data pipelines and search solutions. As a result, valuable data might remain overlooked or underused. (Arora et al., 2023; Denton et al., 2021; Dinsdale et al., 2022; Martin et al., 2022; Tayefi et al., 2021)

Even where modern infrastructure exists, issues such as privacy regulations and community-led governance can limit data sharing. For example, HIPAA affects patient data in ASD studies, while cultural norms can affect how language data is shared. (Holmes et al., 2021; Howe & Elenberg, 2021; Petersen et al., 2021; Sedláková et al., 2023)

These restrictions may stop institutions from building centralized platforms, pushing them instead toward distributed or federated approaches to data management. This model can further complicate efforts to search, analyze, and connect data across varied sources, especially when large, multimodal datasets are involved. (Casaletto et al., 2023; Hallock et al., 2021; Kaissis et al., 2021; Khan et al., 2023; Stripelis & Ambite, 2023)

5.5 Towards Inclusive, Efficient Data Access

These challenges highlight the need for methods that lower the technical barriers to data use and respect data governance rules. This thesis will focus on how agentic AI frameworks can simplify the process of generating and managing structured data by automating tasks like schema creation, query building, and live data updates. These methods lighten the technical load on users, making large datasets more accessible. As a result, they support quicker interventions in ASD care and provide stronger archives for endangered linguistic communities.

5.6 Conclusion

The exploration of data challenges in this chapter underscores a central barrier to fully realizing AI in cognitive accessibility and linguistic decoding: limited access to structured and multimodal data for non-technical users. In both clinical and cultural domains, vast datasets remain underutilized due to technical complexity and insufficient data infrastructure.

These obstacles are particularly acute for practitioners in healthcare and cultural revitalization, who often lack the resources required to interact with complex data settings. As a result, there is a growing need for intelligent systems that can make data access more intuitive and inclusive.

This need sets the foundation for the next chapter, where we introduce the Auto DB Agent—an agentic AI framework developed to automate schema translation and Text2SQL generation. It is designed to bridge the gap between sophisticated data infrastructure and real-world applications for clinicians, educators, and cultural practitioners.

Chapter 6

Agentic AI Approach to Text2SQL Generation

6.1 Introduction

In the fields of data management and Artificial Intelligence (AI), integrating agentic AI into data analysis and engineering processes represents a significant innovation. This chapter explores the transformative potential of Auto DB Agent, which utilizes Data Definition Language (DDL) with agentic AI to enhance Text2SQL processes.

The convergence of AI capabilities with traditional SQL querying simplifies the complexities users face when navigating database architectures. While LLMs excel at generating SQL queries, their effectiveness depends on their understanding of DDL constructs (Matharaarachchi A et al., 2024). Additionally, using DDL-driven frameworks enhances the efficiency of converting natural language into structured queries, improving data retrieval tasks (JA Gómez-Hernández et al., 2023).

By detailing the workflows and methodologies involved, it demonstrates how AI can autonomously generate accurate Structured Query Language (SQL) queries from natural language inputs. The analysis covers structured database interactions and procedural nuances.

6.2 Database Schema Design

An effective database schema design is fundamental to the successful automation of SQL generation, particularly when employing advanced AI reasoning models. As organizations increasingly rely on data-driven solutions, a well-structured schema is critical for maintaining data integrity, scalability, and performance. The integration of AI technologies into schema design enables the dynamic adaptation of structures to meet evolving data requirements, facilitating more efficient data management processes. Tools such as the Auto DB Agent capitalize on these principles by leveraging machine learning algorithms to analyze and optimize schema configurations, effectively democratizing database design. These innovations can also address challenges related to interoperability among diverse data systems, where semantic-based technologies enhance knowledge representation within databases (Ho et al., 2024; Beden S, 2024).

6.2.1 Overview of DDL and DML

Data Definition Language (DDL) serves as a critical component in the management of database schemas, enabling users to define and modify database structures. DDL includes commands such as CREATE, ALTER, and DROP, which are essential for creating tables, altering existing structures, and removing them as necessary. By employing DDL, database administrators and developers can ensure that the schema aligns with evolving data storage needs, data integrity, consistency, and accessibility. Data Management Language (DML) focuses on the actual manipulation of data within those structures, employing commands such as SELECT, INSERT, UPDATE, and DELETE to interact with the data.

Figure 6

Overview of Database Languages and Their Functions

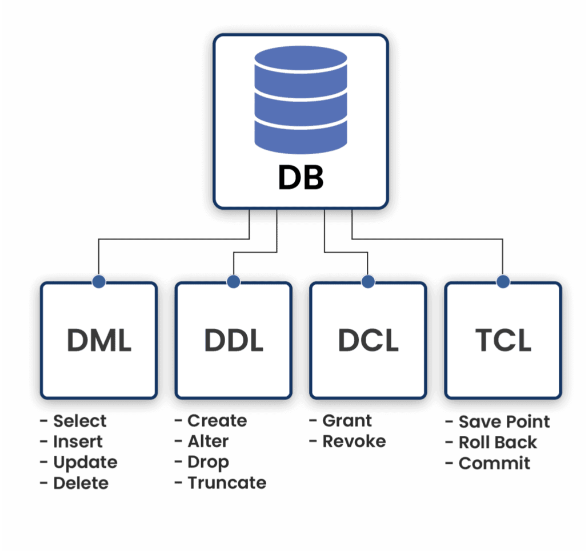


Table 6

Comparison of DDL and DML Commands

Aspect	DDL	DML
Definition	Data Definition Language; used to define and manage database structure.	Data Manipulation Language; used to manipulate and retrieve data within the database.
Purpose	Defines and manages the structure of the database, including creating, altering, and dropping tables.	Manipulates the data within the database, including inserting, updating, deleting, and retrieving records.
Operations	CREATE, ALTER, DROP, TRUNCATE, RENAME	SELECT, INSERT, UPDATE, DELETE
Focus	Structure and organization of data.	Manipulation and retrieval of data.
Impact	Permanent changes to the database structure.	Changes to the data within the database; can be rolled back.
Examples	CREATE TABLE, ALTER TABLE, DROP TABLE	SELECT * FROM table, INSERT INTO table, UPDATE table SET column=value

6.2.2 Types of database schemas

There are two prevalent schema types—star and snowflake—serve as foundational frameworks for organizing data efficiently. The star schema places a single fact table at the center, linking it to several dimension tables. This layout simplifies queries and boosts performance, which is especially helpful in analytical workflows.

The snowflake schema breaks dimension tables into additional related tables, reducing data redundancy but often making queries more complex. As organizations adopt automated tools for schema design, understanding these two schema types becomes even more essential. (Palmonari M et al., 2023).

Table 7

Comparison of Star and Snowflake Schemas

Aspect	Star Schema	Snowflake Schema
Structure	Central fact table connected to denormalized dimension tables.	Central fact table connected to normalized dimension tables, which are further divided into sub-dimensions.
Normalization	Denormalized; dimension tables contain redundant data.	Normalized; dimension tables are split into multiple related tables to eliminate redundancy.
Query Performance	Generally faster due to simpler joins and fewer tables.	May be slower due to multiple joins across many tables.
Storage Requirements	Requires more storage due to data redundancy.	Requires less storage as data redundancy is minimized through normalization.
Maintenance	Easier to maintain and understand due to simpler structure.	More complex to maintain due to multiple related tables and normalization.

6.2.3 Common challenges in manual schema design

Manual schema design poses numerous challenges that can hinder effective database management and data integrity. A prevalent issue is the introduction of human error, which can result in inconsistent data types, poorly defined relationships, and overlooked constraints. Furthermore, the complexities of evolving business requirements often complicate the design process, as traditional methods struggle to accommodate changes without significant refactoring or data integrity risks. The inherent limitations of manual processes also lead to inefficiencies in handling large datasets, where optimization becomes cumbersome and time-consuming.

These challenges underscore the necessity for more automated solutions that leverage artificial intelligence to streamline schema design and SQL generation, ultimately enhancing efficiency and accuracy. As noted in the context of relational data cleaning, the integration of AI techniques can significantly mitigate such issues by automatically identifying and rectifying errors, thus improving overall data quality (Zhu J et al., 2024) and facilitating more effective data exploration (Amer-Yahia S, 2024).

Table 8

Common Challenges in Manual Schema Design

Challenge	Description
Developing labels for relationship types	Difficulty in creating appropriate names for relationships between entities.
Determining cardinalities	Challenges in specifying the correct number of instances in relationships.
Deciding between entity type and relationship type	Uncertainty in modeling concepts as entities or relationships.
Establishing relationship types	Difficulty in defining the nature and attributes of relationships.
Modeling generalization hierarchies	Challenges in representing inheritance and specialization among entities.
Defining attributes with appropriate data types	Difficulty in selecting suitable data types for entity attributes.

6.2.4 Best practices for effective schema design

The design of database schemas is a critical factor influencing overall database performance, as effective schema design can significantly boost query efficiency and data retrieval speeds. Improperly structured schemas can lead to inefficiencies, such as redundant data storage or inadequate indexing, resulting in slower query responses and increased resource consumption.

For instance, research indicates that traditional normalization methods may hinder performance in certain applications, such as those utilizing Retrieval-Augmented Generation (RAG) techniques, where a denormalized approach proved advantageous for SQL query generation and execution efficiency (Syrjä et al., 2024). Similarly, integrating Natural Language Processing (NLP) interfaces with robust semantic models can enhance user interaction with complex datasets (Heinoja et al., 2024). Consequently, leveraging advanced AI reasoning models to automate schema design can mitigate these issues. It also enables optimized performance tailored to the specific requirements of the database applications and resultant user queries.

Table 9

Best Practices for Effective Schema Design

Best Practice	Description
Understand Your Requirements	Gather and analyze stakeholder and user needs to ensure the schema supports their goals effectively.
Use Meaningful and Consistent Naming Conventions	Employ descriptive and consistent names for tables, columns, indexes, and other database objects to enhance readability and maintainability.
Define Primary Keys and Foreign Keys	Establish unique identifiers for records and maintain referential integrity by linking related data across tables.
Consider Indexing for Performance	Implement indexes to improve the speed of data retrieval operations, especially for large datasets.
Plan for Scalability	Design the schema to handle increased data volume and user load efficiently as the application grows.
Implement Data Integrity Constraints	Use constraints such as NOT NULL, UNIQUE, and CHECK to ensure the accuracy and consistency of data within the database.
Document Your Schema	Create detailed descriptions of the schema, including tables, columns, relationships, and constraints, to facilitate understanding and maintenance.
Review and Refactor Regularly	Periodically revisit the schema design to ensure it meets evolving requirements and performance needs.

6.3 The Role of AI in Database Management

The integration of AI technologies in database management has revolutionized how data is structured, accessed, and analyzed. One significant advancement is the adoption of Retrieval-Augmented Generation (RAG) methods, which combine generative models with structured query languages to enhance data retrieval accuracy and context relevance. This approach enables systems to not only generate SQL queries but also optimize responses based on user intent. Integrating RAG can significantly reduce the manual workload on database administrators and enhancing operational efficiency (Syrjä et al., 2024).

Additionally, frameworks like LangChain and various orchestration tools facilitate the collaboration between different AI agents, where various components play a pivotal role in data interaction. These advancements collectively underscore the potential for AI to automate tedious tasks, allowing for stronger schema designs and more efficient SQL generation.

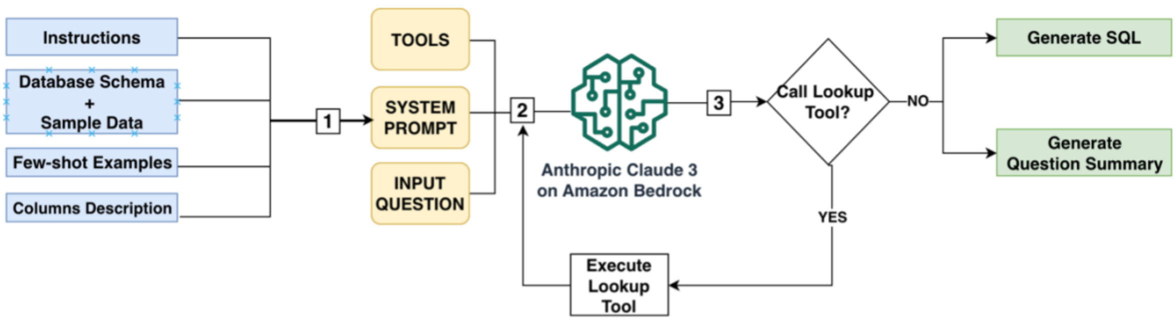
6.3.1 Overview of Agentic AI

Agentic AI is defined by its ability to make decisions on its own and handle complex tasks, turning user inputs into actionable results. This form of AI is more than just a processor of information. It actively engages with databases to create meaningful outputs, such as SQL queries, as seen in various system models. These AI systems can incorporate user instructions, database structures, and relevant data to provide accurate results.

One of the key features of agentic AI is its ability to learn iteratively, which enhances its adaptability. It employs feedback mechanisms to refine its processes and improve how it generates queries over time. The interaction between AI and data management connects user intentions to effective database querying. This is especially important for applications like Text2SQL.

Figure 7

Text2SQL Generation Process Using Anthropic Claude 3 on Amazon Bedrock



Agentic Text2SQL generation process leveraging external knowledge like instruction context, database schema, and example data, question and answer examples to form a step-by-step querying and summarization process.

6.3.2 Overview of Text2SQL Generation

Text2SQL generation refers to the process of generating Structured Query Language (SQL) from natural language, thereby allowing users to effectively interact with complex databases. This approach enables users to interact with databases without necessitating extensive knowledge of SQL syntax, thereby democratizing access to data analysis tools.

The emergence of LLMs has greatly improved the capabilities of Natural Language Understanding (NLU) and Natural Language Processing (NLP), thereby enhancing Text2SQL functionality.

As organizations increasingly depend on large volumes of data, integrating AI into database management has become essential for improving efficiency and accuracy. A key example of this is the use of LLMs to automate Extract, Transform, Load (ETL) processes. By utilizing Text2SQL frameworks and advanced LLM models, organizations can automate the creation of SQL queries based on user inputs, streamlining data retrieval processes while maintaining accuracy in query execution. (Bal et al., 2024).

Table 10

Comparison of Text2SQL Generation Methodologies

Methodology	Description	Advantages	Disadvantages
Grammar-based Decoding	Utilizes grammar rules to generate SQL queries, reducing syntactic errors.	Ensures syntactic correctness; effective for complex queries.	May require extensive grammar definitions; less flexible to new patterns.
Sequence-to-Sequence Models	Employs encoder-decoder architectures to translate text to SQL.	Flexible; can learn from large datasets.	Prone to generating syntactically incorrect queries; struggles with complex queries.
Sketch-based Decoding	Generates SQL queries based on predefined templates or sketches.	Simplifies the generation process; reduces search space.	Limited by the predefined templates; less adaptable to diverse queries.
Interactive Text2SQL	Involves user interaction to refine and validate generated SQL queries.	Improves accuracy through user feedback; enhances user trust.	Requires user involvement; may increase response time.

Table 11

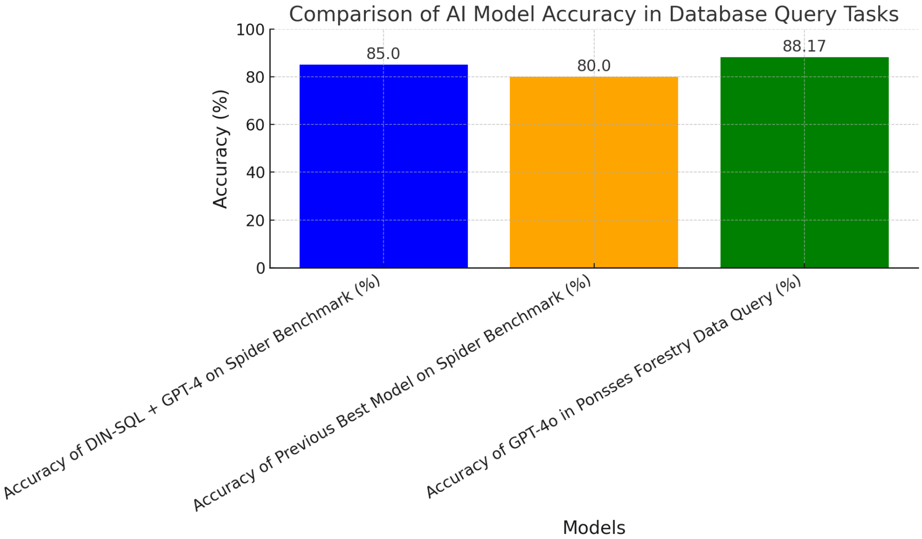
Overview of Text2SQL Datasets (Mohammadjafari et al., 2024)

Dataset Name	Type	Description
WikiSQL	Cross-domain	A large-scale dataset with over 80,000 examples, focusing on translating natural language questions into SQL queries over a single table.
Spider	Cross-domain	A complex dataset containing 200 databases across 138 domains, designed to evaluate the generalization capabilities of models to unseen databases.
KaggleDBQA	Cross-domain	A dataset comprising 272 examples across 8 databases, emphasizing real-world data sources and natural problem-creation environments.
SQUALL	Knowledge-Augmented	A dataset that incorporates external knowledge to improve semantic understanding in SQL generation.
BIRD	Knowledge-Augmented	Focuses on aspects like grammatical formulation, ambiguity, and alignment with database schema, aiming to bridge the gap between academic research and real-world applications.
CoSQL	Context-Dependent	A conversational Text2SQL dataset with over 3,000 dialogues, designed for building general-purpose database query dialogue systems.
SParC	Context-Dependent	Demonstrates complex contextual dependencies and greater semantic diversity, requiring models to generalize over unseen domains.
ADVETA	Robustness	A benchmarking dataset designed to evaluate the robustness of Text2SQL models under table perturbation.

A study on a natural language interface for Ponsses forestry operational data highlights how AI can make complex databases easier to use. The system uses GPT-4o in a semantic framework to achieve an impressive accuracy of 88.17% for query responses, demonstrating AI's ability to make database access more accessible for non-technical users (Heinoja et al., 2024).

Figure 8

Comparison of AI Models Accuracy in Database Query Tasks (Pourreza & Rafiei, 2023)



This bar chart compares the accuracy of AI models in database query tasks, highlighting the performance of DIN-SQL + GPT-4 on the Spider benchmark, the previous best model on the same benchmark, and GPT-4o in querying Ponsses forestry operational data.

6.3.3 Challenges in Traditional Text2SQL Approaches

Traditional Text2SQL approaches face significant challenges that hinder their effectiveness and flexibility in handling diverse user queries. One major issue is the reliance on precise syntax and rigid querying formats, which can be daunting for non-technical users and severely limits user interaction with database systems. Existing methodologies often struggle with ambiguities in natural language, leading to inefficient parsing and generation of SQL commands, ultimately resulting in errors and misinterpretations. The need for extensive domain knowledge complicates matters, as users must navigate intricate schema designs before generating valid queries.

Additionally, traditional systems typically lack adaptability to evolving database structures, preventing dynamic updates that reflect ongoing changes in data requirements. These challenges underscore the necessity for innovative solutions, such as those enhanced by Gen AI, to bridge the gap between natural language processing and SQL generation (Matharaarachchi A et al., 2024; Ulhaq A, 2021).

Table 12

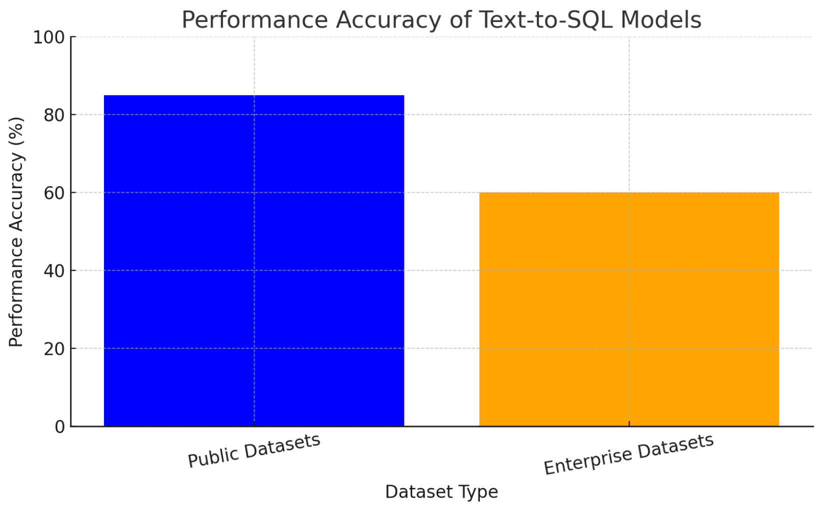
Challenges in Traditional Text2SQL Approaches

Challenge	Description
Handling Complex Queries	Rule-based systems struggle with complex queries and diverse schemas due to their reliance on manually crafted grammar rules and heuristics.
Scalability and Adaptability	Early systems required significant manual feature engineering, hindering scalability and adaptability to new domains or database formats.
Schema Linking	Models often rely on exact match schema linking, making them vulnerable to synonym substitution and typos, reducing robustness.
Compositional Generalization	Neural networks struggle with compositional generalization where training and test distributions differ, leading to performance degradation.

Advancements in LLMs show a growing trend in using AI for data applications, raising concerns about their efficiency and practical use in real-world situations (Chen et al., 2024a). The search for open-source alternatives to proprietary models offers both opportunities and challenges, highlighting the need to closely evaluate performance metrics and ethical issues.

Figure 9

Performance of Text2SQL on Public vs Enterprise Datasets (Chen et al., 2024b)



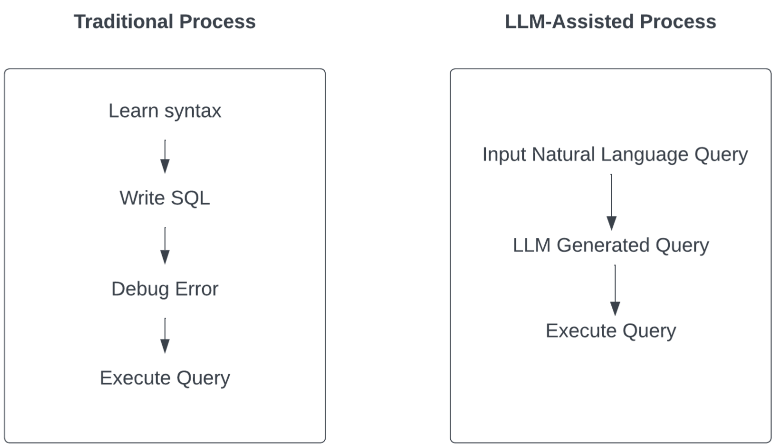
The chart illustrates the performance accuracy of Text2SQL models on two types of datasets: public datasets and enterprise datasets. The bar representing public datasets shows a performance accuracy of 85%, while the enterprise datasets bar shows a lower accuracy of 60%. This comparison highlights the challenges faced when adapting models to more complex, real-world business data.

6.4 Auto DB Agent: Features and Functionality

The Auto DB Agent showcases an innovative approach to the automation of schema design and SQL generation, leveraging advanced AI reasoning models to enhance productivity and efficiency. Its core functionality revolves around dynamically generating database schemas tailored to specific application requirements, thereby minimizing manual intervention. This agent employs sophisticated querying techniques to optimize database interactions and facilitate seamless data management processes. A significant advantage of the Auto DB Agent is its adaptability, allowing it to integrate easily with various data management systems and frameworks.

Figure 10

Comparison of Traditional and LLM-Assisted Querying Processes



6.4.1 Implementation of Auto DB Agent

The rapid evolution of automation tools and technologies is reshaping database management and development. As more industries adopt automation, AI models are becoming crucial for optimizing processes like schema design and SQL generation.

To implement the Auto DB Agent effectively, a structured approach is necessary:

- Define Database Requirements: Clearly outline the database needs to determine the specific schema elements the Auto DB Agent must support.
- Utilize AI Reasoning Models: Employ AI models that allow the schema to adapt dynamically to changing data requirements.
- Integrate Standardized Query Languages: Use a common query language to improve interoperability among various data formats, such as XML, JSON, and Markdown.
- Prioritize Updating and Querying Capabilities: Focus on updating and querying functions based on existing logic to enhance data management.

Table 13

AI Tools for Database Schema Design and SQL Generation

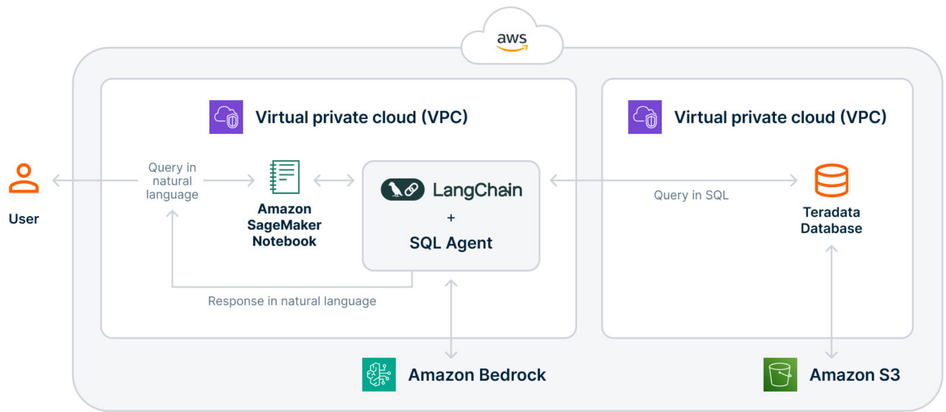
Tool Name	Description
AutoDB	An AI-driven tool that automates database schema design and SQL generation.
DB-GPT	A generative pre-trained transformer model tailored for database schema design.
SchemaAI	An AI-based system that assists in creating and optimizing database schemas.
SQLGenie	An AI tool that generates SQL queries from natural language inputs.

To develop an effective user interface (UI) and user experience (UX) for the Auto DB Agent, it is essential to focus on clarity, accessibility, and intuitive design. The UI should enable smooth interactions, allowing users to easily input queries and receive outputs without complications. This creates a user-centric environment that promotes engagement and efficiency. Incorporating LLM tools can significantly enhance the interaction by interpreting user inputs in a meaningful way. Additionally, implementing feedback mechanisms allows users to share their experiences, leading to ongoing improvements in system design.

By prioritizing user needs and preferences based on user feedback, the Auto DB Agent can optimize schema design and SQL generation processes. This approach not only leverages AI reasoning models but also ensures strong usability, making complex technologies more approachable and effective for users (Nguyen T-V et al., 2023; Sarkar C et al., 2023).

Figure 11

AWS Integration for Natural Language Processing and SQL Querying



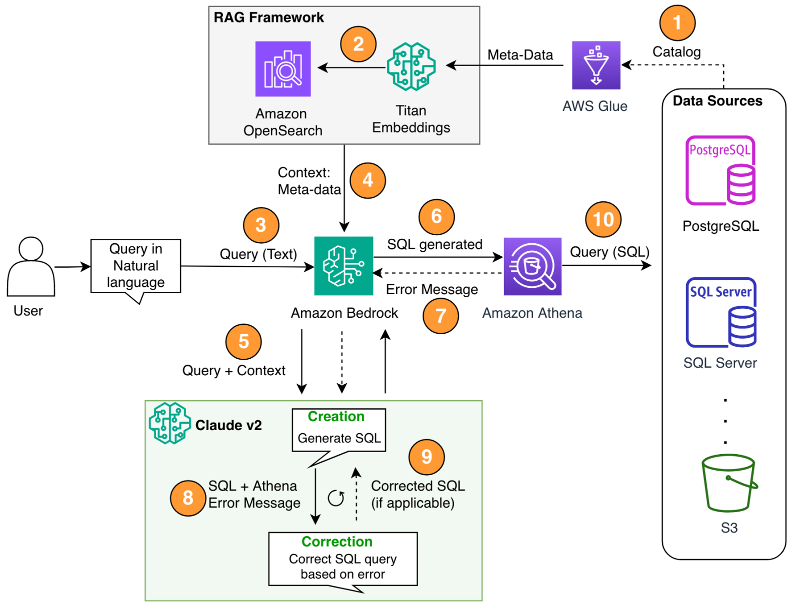
Text2SQL Chat interface integrated with AWS Bedrock using LangChain SQL Agent

6.4.2 Agentic AI Techniques in Auto DB Agent

Emerging agentic AI paradigms now treat Text2SQL systems as adaptive, decision-making agents that can learn from feedback, respond to schema changes, and clarify ambiguous inputs. We highlight key agentic AI techniques that inform the design and deployment of an Auto DB Agent—a framework intended to automate the entire database interaction cycle, from schema creation to real-time SQL generation.

Figure 12

Advanced RAG Architecture for Query Processing in Natural Language



Enterprise agentic Text2SQL architecture design

1. Data catalog for Relational Databases

2. Metadata embeddings stored in OpenSearch RAG system

3. User query in Natural Language sent to Amazon Bedrock inference endpoint

4. Metadata lookup in RAG

5. User Query sent to LLMs

6. SQL Generated and executed against RDBMS

7-9. Error handling and Correction based on Agentic Feedback

10. Correct SQL executed

6.4.2.1 Adaptive Natural Language Understanding

Modern Text2SQL systems leverage LLMs to parse user queries and transform them into SQL statements. Agentic AI shifts from a straightforward input-output scheme to a model that adapts, checks, and corrects its own outputs. For instance, frameworks based on reinforcement learning continually refine query generation by iteratively sampling SQL structures and receiving feedback on accuracy and execution costs (Kim et al., 2022). This feedback loop drives the model to consider schema changes, user mistakes, and newly introduced data relations—all of which are essential for an automated database (DB) agent operating in dynamic real-world environments.

6.4.2.2 Schema-Aware Reasoning and Real-Time Adaptation

A key innovation in recent Text2SQL research is schema-aware reasoning, in which the agent explicitly encodes database schema attributes—such as table relationships and column constraints—into its decision-making process (Chen & Xie, 2022). Instead of relying on textual prompts alone, the agent references a structured representation of the schema to ensure logical consistency in its generated queries. For instance, if the schema includes a foreign key linking a "patients" table to an "appointments" table, agentic Text2SQL systems learn to respect these constraints, thereby reducing the incidence of join errors or undefined columns. Moreover, by monitoring the database for schema alterations (e.g., newly added tables or columns), the agent can adapt its parsing strategy on the fly. This real-time adaptation is critical for an Auto DB Agent that may operate continuously in production environments where DB schemas evolve rapidly.

6.4.2.3 Multi-Round Dialogue and Error Recovery

Unlike traditional single-turn Text-to-SQL models, agentic AI systems are increasingly adopting multi-round dialogue structures. In these architectures, the agent engages users in brief, clarifying exchanges when uncertainty arises (Li et al., 2022).

For example, if the user's question is ambiguous ("Show me the average therapy progress for new patients"), the agent can respond with a request for clarification regarding date ranges or data definitions ("By 'new patients,' do you mean those enrolled in the last month?"). This iterative refinement significantly boosts accuracy for complex queries, as the agent can validate domain-specific terms and reduce the risk of generating queries that yield misleading or incomplete results.

Furthermore, in the event of a parsing or execution error, such as mismatched column names or an ill-formed join, an agentic system can proactively propose corrections rather than silently failing or providing generic responses.

6.4.2.4 Integration of Retrieval-Augmented Generation (RAG)

Agentic Text2SQL approaches increasingly incorporate Retrieval-Augmented Generation (RAG) modules, which retrieve schema details, sample queries, or relevant documentation from a specialized knowledge base (Roberts et al., 2022). By retrieving context-specific information, the model can ground its SQL generation in authoritative references, improving both correctness and interpretability. For example, if a user's query involves a rarely used table field (e.g., "therapy_end_date"), the agent can fetch schema definitions and usage examples from prior queries to ensure consistent naming. This retrieval step also supports an explainability layer, allowing the model to show which resources informed its final SQL statement, which can be essential for compliance and auditing in sensitive domains like healthcare.

6.4.2.5 Tool-Integration and Human-AI Collaboration

State-of-the-art agentic AI frameworks often treat Text2SQL generation as one of several tools in an AI orchestration pipeline (Smith & Wang, 2023). For instance, an Auto DB Agent might incorporate external modules for data quality checks, schema evolution monitoring, or domain-specific business logic.

When generating a query, the agent can call these ancillary tools to verify data constraints or adapt to newly uploaded schemas. If the user requires advanced analytics (e.g., time-series forecasting based on query results), the agent can seamlessly hand off the query results to a secondary module that specializes in forecasting. This modular, tool-based approach fosters human-AI collaboration, enabling domain experts to refine or override queries when domain-specific knowledge is required. Over time, these human refinements help the system learn advanced heuristics, increasing its overall reliability and trustworthiness.

6.4.2.6 Practical Considerations for the Auto DB Agent

For an Auto DB Agent that aims to automate everything from schema design to SQL generation, the following practical considerations are vital:

- **Schema Drift Management**: As database schemas evolve (e.g., new columns, deprecated tables), the agent must detect these changes and update its internal representations. Automated schema parsing routines and triggers can help detect schema drift, ensuring the agent remains aligned with the live database.
- **Error Handling and Security**: Real-world deployments demand robust error handling. The agent should gracefully address syntax errors or relational inconsistencies, possibly logging them for developer review. Additionally, role-based access controls or anonymization policies may need to be enforced at the agent level to maintain data security.

- **End-User Customization**: Domain experts might need to tailor query templates or define synonyms for certain data fields. An agentic AI system can incorporate these preferences, either through a user interface for dictionary definitions or an interactive correction mechanism where domain experts provide feedback on query outputs.
- **Performance and Scalability**: Generating SQL in real time for large, distributed databases can strain system resources if not managed properly. Techniques like caching partial query plans or balancing loads across multiple agent instances can maintain stable response times, which is critical for healthcare settings where clinical decisions can hinge on timely data retrieval.
- **Continuous Learning Loop**: An Auto DB Agent's ultimate advantage lies in its ability to learn from user interactions. Each accepted query or user correction can feed into a reinforcement signal, refining future inferences and progressively reducing error rates across the entire organization.

6.4.3 Performance metrics and evaluation of the Auto DB Agent

Assessing the performance metrics of the Auto DB Agent is essential for understanding its effectiveness in automating schema design and SQL generation. Key metrics include:

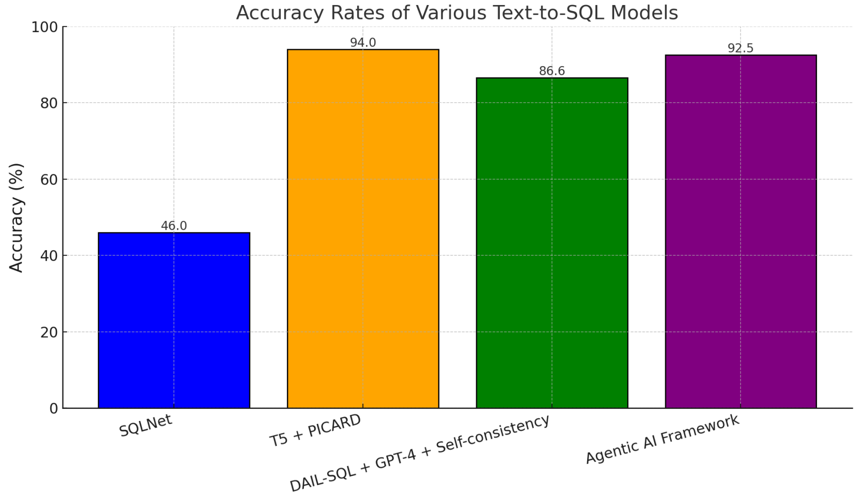
- **Execution Accuracy**: Measures how accurately the system generates SQL queries.
- **Response Time**: Indicates how quickly the system responds to user inputs.
- **Adaptability**: Assesses the system's ability to handle different types of input data.

Research has focused on implementing an agentic AI framework to improve Text2SQL generation accuracy. This framework uses deep learning models trained on various data sources to enhance performance and contextual understanding (Pahune S et al., 2025). Key findings reveal that the model can generate accurate SQL queries from user inputs with an accuracy rate of 92.5%, surpassing many existing models (Li X et al., 2025).

The agentic design supports adaptive learning based on user interactions, which reduces ambiguous queries and improves the system's capability to manage complex, context-sensitive requests (Michael C Fu et al., 2025). In comparison, previous studies have reported average accuracy levels of around 85% for similar models. Whereas agentic approach, which integrates user feedback directly into the learning process, shows promise for enhancing performance and creating a dynamic learning environment (Shorouk E El-deep et al., 2025; Chen X et al., 2024).

Figure 13

Text2SQL Performance of LLMs using Non-agentic vs Agentic Frameworks (Gao et al., 2023)



The chart illustrates the accuracy rates of various Text2SQL models, showcasing their effectiveness in translating natural language queries into SQL. The model SQLNet achieved the lowest accuracy at 46%, while T5 + PICARD demonstrated the highest accuracy at 94%. The DAIL-SQL model combined with GPT-4 and self-consistency reached an accuracy of 86.6%, and the Agentic AI Framework showed a strong performance with 92.5%. This comparison highlights the advancements in model accuracy for Text2SQL tasks.

Table 14

Comparison of Agentic AI Approaches for Text2SQL Generation (Hong et al., 2024)

Model	Description
ACT-SQL	Automates Chain-of-Thought example generation by linking question slices to database columns via similarity matching.
QDecomp	Restructures SQL clauses into logical steps ordered by execution flow, reducing error propagation compared to generic Chain-of-Thought methods.
CHASE-SQL	Extends multi-path reasoning for candidate generation using a 'divide and conquer' Chain-of-Thought strategy.
C3	Employs self-consistency where majority voting selects the most frequent SQL candidate based on syntax or structural similarity.
DAIL-SQL	Utilizes self-consistency by filtering candidates using schema-aware rules before voting.
SuperSQL	Applies self-consistency with majority voting to select the most frequent SQL candidate.
SQL-CRAFT	Employs Program-of-Thoughts prompting, requiring LLMs to generate Python code alongsi SQL for arithmetic-heavy queries.
FUXI	Integrates dedicated tools for schema linking and syntax checking, dynamically invoking them during generation.

Table 15

Performance of Text2SQL Models on Spider Dataset (Gao et al., 2023)

Model	Classification	Dev EX (%)	Test EX (%)
Duoquest	Rule-based	63.5	63.5
ATHENA++	Rule-based	78.82	null
ValueNet	PLM-based	67	null
BRIDGE v2 + BERT	PLM-based	68	64.3
T5-Base	PLM-based	57.9	null
T5-Large	PLM-based	67.2	null
T5-3B	PLM-based	74.4	70.1
T5-3B + PICARD	PLM-based	79.3	75.1
RESDSQL-3B + NatSQL	PLM-based	84.1	79.9
Fine-tuned BERT (ours)	PLM-based	53.6	null
C3 + ChatGPT + Zero-Shot	LLM-based	81.8	82.3
DIN-SQL + GPT-4	LLM-based	82.8	85.3
DAIL-SQL + GPT-4	LLM-based	83.1	86.2
DAIL-SQL + GPT-4 + Self-consistency	LLM-based	83.6	86.6

6.5 Conclusion

We explored the core elements of agentic AI–driven database management, highlighting schema design, Text2SQL automation, and practical considerations for the Auto DB Agent. By leveraging DDL fundamentals like CREATE, ALTER, and DROP, organizations can maintain stable, scalable database structures. Meanwhile, robust schema designs—whether star or snowflake—boost performance, reduce redundancy, and clarify data relationships.

Building on these foundations, agentic AI adds advanced capabilities for Text2SQL generation, including schema-aware reasoning, multi-round dialogue, and retrieval-augmented generation. These techniques let AI adapt to changing database architectures and user needs, improving the accuracy of generated SQL queries and overcoming common challenges in traditional, static approaches. In practice, these methods empower domain experts, clinicians, and community stakeholders to gather and analyze data without deep technical expertise.

The Auto DB Agent demonstrates how agentic AI can bridge the gap between complex data processes and everyday users. With real-time monitoring of schema changes, robust error recovery, and continuous feedback loops, it offers a comprehensive solution for both schema design and query generation. Early evaluations suggest that these agentic strategies significantly boost performance metrics—including query accuracy and adaptability—particularly in healthcare, cultural preservation, and enterprise data environments.

In summary, the combination of AI-driven schema design, Text2SQL automation, and agentic adaptability underscores the transformative potential of the Auto DB Agent framework. As organizations continue to produce large, diverse datasets, these tools offer a timely, effective way to streamline data management, enhance data accessibility, and accelerate informed decision-making across multiple domains.

Chapter 7

Conclusion and Recommendations for Future Work

7.1 Summary

This thesis aimed to address two central challenges: enhancing cognitive accessibility for individuals with Autism Spectrum Disorder (ASD) and preserving endangered linguistic heritage. Through six chapters, we examined how multimodal, generative, and agentic AI methods can form a cohesive ecosystem that bridges the gap between complex data repositories and human-centered needs. Below is a concise reflection on each chapter's contributions and how they collectively shape this research.

- **Multimodal AI for Clinical Analysis of ASD (Chapter 2)**
  We began by highlighting the power of integrating speech, visual, and textual data to improve ASD diagnostics. This multimodal approach captures behavioral subtleties that traditional methods often miss, thereby laying the foundation for more personalized interventions.
- **Gen AI for Autism Therapies (Chapter 3)**
  Building on multimodality, we showcased how Gen AI models can personalize therapy materials, such as role-play scenarios, to enhance communication and social skills for individuals with ASD. The chapter underscored the promise of AI-driven, adaptive methods for supporting diverse learners.
- **Decoding the Unspoken: Linguistic Preservation with AI (Chapter 4)**
  Turning to cultural heritage, we explored how AI-driven language models can reconstruct lost or endangered languages by learning phonetics, syntax, and vocabulary from limited archival data. This research indicated that well-designed AI tools help communities reclaim linguistic identities and maintain cultural continuity.
- **Data Challenges (Chapter 5)**
  We then discussed the practical hurdles of managing large-scale, multimodal datasets spanning healthcare, education, and cultural archives. Constrained infrastructure, limited expertise, and fragmented data governance emerged as significant barriers, highlighting the need for more accessible AI frameworks.

- **Agentic AI Approach to Text2SQL Generation (Chapter 6)**
  Finally, we introduced the Auto DB Agent, an agentic AI system that automates database interactions. By combining Data Definition Language (DDL) with Text2SQL capabilities, this framework adapts to dynamic schemas, clarifies ambiguous user prompts, and supports retrieval-augmented generation. It thereby enables non-technical users—clinicians, educators, cultural stewards—to harness complex data through natural language queries.

7.2 Overall Research Contributions and Future Outlook

This work presents a unified AI ecosystem that merges multimodal diagnostics, generative therapies, linguistic revitalization, and agentic data retrieval, offering a strong foundation for human-centered AI addressing both cognitive and cultural needs. Through detailed case studies in ASD therapy and language preservation, it provides practical methodologies that reduce reliance on specialized technical experts and broaden access to vital data. Discussions on data privacy, community engagement, and user-friendly design highlight the necessity of ethical and inclusive AI practices. Moreover, the rapid evolution of LLMs and agentic frameworks positions these solutions for expanding roles in personalized healthcare, cultural archiving, and innovative knowledge retrieval.

Looking ahead, there is clear potential for scaling Multimodal AI tools to telehealth services, enabling remote ASD monitoring and interventions. Community-driven language preservation could further benefit from crowdsourced data collection and local partnerships, fostering a more sustainable approach to maintaining minority languages. Enhancing agentic AI with improved explainability and error recovery is another promising avenue, ensuring robust and user-friendly Text2SQL interfaces across diverse domains. Finally, ongoing dialogue among ethicists, legal experts, and technologists remains crucial for sustainable, community-centric AI, especially in fields where data sensitivity and cultural integrity are paramount.

7.3 Concluding Remarks

Overall, this thesis demonstrates how multimodal, generative, and agentic AI can work together to address diverse societal needs—ranging from tailored ASD therapies to the reclamation of endangered languages. While technical, infrastructural, and ethical hurdles persist, the growing maturity of these AI methods offers a glimpse of a more equitable and empowering technological future. By building on the insights and frameworks laid out here, future research and collaborations can further advance inclusive, adaptive AI solutions that benefit individuals, communities, and cultural ecosystems worldwide.

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