AI-Powered Learning: A Design Study Creating an Adaptive Intelligent Tutoring System for ADHD Learners

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Abstract

Problem definition. Standard educational approaches often fail to meet the specific needs of individuals with Attention-Deficit/Hyperactivity Disorder (ADHD), who experience challenges with inattention, executive functioning, and self-regulation in traditional learning environments. This creates a need for educational tools that provide structured, engaging, and personalised support to mitigate cognitive overload. This design study addresses this issue by evaluating "Jabari," an adaptive Intelligent Tutoring System (ITS) powered by a Large Language Model (LLM), created to personalise the learning experience for adults with ADHD in real-time.

Methodology. This study employed a between-subjects A/B testing design to compare an adaptive version of the ITS against a non-adaptive control version. The study measured user trait profiles, cognitive load (NASA-TLX), user satisfaction, and learning performance.

Results & Theoretical Contribution. The adaptive ITS significantly improved user trait profiles, most notably by reducing inattention and impulsivity while increasing confidence and motivation, while also lowering the perceived cognitive load for participants. However, these benefits did not translate into statistically significant improvements in user satisfaction or learning performance. This finding contributes to the literature by demonstrating the partial efficacy of such systems, revealing a disconnect between influencing a user's internal state and affecting external outcomes like learning and satisfaction.

Managerial implications. For developers of educational technology and instructional designers, this study reveals that while trait-based AI adaptation can successfully reduce cognitive load and improve the internal state of neurodivergent users, these benefits do not automatically guarantee better learning outcomes or higher satisfaction. Future designs should consider not only alleviating cognitive strain but also incorporating strategies to ensure that learners remain sufficiently challenged and internal motivation is stimulated to facilitate cognitive processing and knowledge retention.

Keywords. AI-Powered Learning, Intelligent Tutoring System (ITS), ADHD, Adaptive Learning, Large Language Models (LLMs), Personalised Education, Cognitive Load, Design Study

1 Introduction

The human brain comprises a complex network of approximately 86 billion neurons, leading to a wide range of information processing capabilities. This neurological diversity means that learning experiences are profoundly individual (Allen, 2015). For those who are neurodivergent, especially individuals with Attention-Deficit/Hyperactivity Disorder (ADHD), this diversity becomes even more apparent. Learners with ADHD exhibit a unique spectrum of cognitive and emotional responses (Adler et al., 2017; Mostert et al., 2015), making their educational needs distinct and varied. As a result, standard educational approaches often struggle to meet their specific learning styles and requirements (Varrasi et al., 2022; Zentall, 2005).

Individuals with ADHD generally encounter significant challenges in traditional learning environments (Barkley, 2015). Symptoms such as inattention (Belmar Mellado et al., 2013), difficulties with executive functioning (Doyle, 2006; Pievsky & McGrath, 2018), and issues with self-regulation (Barkley, 1997; Shaw et al., 2014) can significantly impact academic performance and task completion. These challenges are not due to a lack of ability but arise from a mismatch between conventional teaching methods and the unique learning needs exhibited by individuals with ADHD (Higgins, 2007). Hence, there is an urgent need for educational tools designed specifically for these learners, which offer structured support (Parker & Boutelle, 2009), lessen cognitive overload (Forster et al., 2013; Kahn et al., 1990), and improve engagement (Lorch et al., 2006).

Intelligent Tutoring Systems (ITS) offer a practical solution for personalised education (Al-Emran & Shaalan, 2014; Rizvi, 2023). By employing artificial intelligence, ITS can simulate human tutoring by delivering tailored instruction, feedback, and support (Hafidi & Bensebaa, 2014). The introduction of Large Language Models (LLMs) has further enriched the capabilities of ITS, enabling a better understanding of student input, dynamic content generation, and adaptive interaction strategies (Cheng et al., 2024; Morales-Chan et al., 2024). This thesis seeks to utilise these LLM capabilities to develop an ITS specifically addressing the learning challenges frequently experienced by students with ADHD.

This study explores the capabilities of "Jabari," an LLM-powered Intelligent Tutoring System (ITS) designed to help learners with ADHD in second language acquisition. The aim is to create a responsive learning environment that adapts in real-time to users' cognitive and emotional states by modifying instructions and feedback. This research evaluates the effectiveness of these adaptive features through a controlled experiment comparing the learning performance, user satisfaction, cognitive load, and trait profiles of adults with ADHD using the adaptive ITS versus those using a non-adaptive control version.

2 Literature Review

This chapter provides a comprehensive review of the literature relevant to designing and evaluating an adaptive intelligent tutoring system for learners with ADHD. It begins by exploring the characteristics of ADHD in adulthood, followed by an examination of learning strategies for this population. The chapter then delves into adaptive learning principles through an ITS and the transformative potential of LLMs in education. Finally, it discusses current methodologies in evaluating AI interventions for ADHD, identifying critical literature gaps.

2.1 Understanding ADHD

2.1.1 ADHD

ADHD is a neurodevelopmental condition characterised by persistent inattention and/or hyperactivity-impulsivity that disrupts functioning or development. It appears in three main types: inattentive, which involves difficulty sustaining focus and organising tasks, hyperactive-impulsive, marked by excessive movement and impulsivity (Pievsky & McGrath, 2018), and a combined type that lends symptoms from both subtypes. Individuals with inattentive symptoms often struggle with working memory and processing complex information, which directly increases cognitive load (Kusumasari et al., 2018; Salomone et al., 2016). Attention deficits may stem from difficulties in engaging top-down cognitive control, forcing greater mental effort to stay on task (Friedman-Hill et al., 2010). For the hyperactive-impulsive subtype, overt physical hyperactivity in childhood often transitions to a sense of inner restlessness in adults (Cubbin et al., 2020). This subtype is characterised by deficits in attentional, motor, and cognitive impulsivity, which can impact decision-making (Malloy-Diniz et al., 2007).

A review by Pievsky and McGrath (2018) found that individuals with ADHD have impairments in critical cognitive functions like working memory, sustained attention, and response inhibition, as well as increased variability in reaction times. Neurobiologically, neurotransmitters such as dopamine and norepinephrine play a role, with theories proposing that lower baseline arousal in ADHD brains may lead to distractibility and a greater need for external stimulation to maintain optimal focus (Söderlund et al., 2007). Sensory processing is often affected, with many individuals with ADHD exhibiting heightened sensitivity to extraneous stimuli, which further contributes to distraction (Forster et al., 2013). Additionally, emotional dysregulation is common throughout the lifespan for individuals with ADHD, where strong feelings of frustration or boredom can derail cognitive efforts and task engagement (Shaw et al., 2014). Understanding these neurobiological and cognitive aspects is crucial for creating effective interventions that tackle the specific learning challenges faced by adults with ADHD.

2.1.2 Core symptoms of ADHD in adulthood

The expression of ADHD symptoms evolves with age, and adults with ADHD present unique manifestations that require an understanding beyond childhood presentations (Adler et al., 2017; Asherson et al., 2014). Inattention in adulthood often translates into difficulties focusing on tasks and completing larger projects, impacting academic and professional areas (Olagunju & Ghoddusi, 1994; Pinho & Coutinho, 2024). Additionally, executive dysfunction, encompassing difficulties with planning, organisation, and working memory, is increasingly recognised as a central feature of adult ADHD (Adler et al., 2017).

Hyperactivity, a prominent symptom in childhood ADHD, tends to present differently in adults (Agarwal et al., 2016; Cubbin et al., 2020). Overt physical hyperactivity may decrease, often replaced by an inner sense of restlessness, fidgeting, or an inability to relax (Cubbin et al., 2020; Baskaran et al., 2020). Adults might exhibit workaholic tendencies or find it challenging to sit through lengthy meetings (Agarwal et al., 2016). Furthermore, adults with ADHD often show deficits in attentional, motor, and cognitive impulsivity, which can impact decision-making processes, interpersonal relationships, and overall daily functioning (Fernandes Malloy‐Diniz et al., 2007; Almeida Rocha et al., 2024).

2.1.3 Executive functioning

Executive functions (EFs) are a set of higher-level cognitive processes essential for goal-directed behaviour, and are considered by many to be a central characteristic of ADHD (Sinha et al., 2008). Specific EF deficits commonly observed in adults with ADHD include impairments in working memory (difficulty holding and manipulating information), planning and organisation (challenges in setting goals, structuring tasks, managing time), inhibition (difficulty controlling impulses and resisting distractions), and cognitive flexibility (struggles adapting to changing demands and generating alternative solutions) (Barkley, 2010; Fabio & Caprì, 2017; Johnson & Reid, 2011; Ağayeva, 2024).

2.1.4 Diagnosing ADHD in adulthood

Diagnosing ADHD in adults presents unique challenges, as symptom manifestation evolves with age, and executive dysfunction becomes more prominent (Adler, 2004; Adler et al., 2017). ADHD frequently co-occurs with other mental health conditions such as anxiety disorders, depression, substance use disorders, and learning disabilities, making differential diagnosis critical (Masi, 2015; Piñeiro-Dieguez et al., 2014; Magon & Müller, 2012; Montano & Weisler, 2011; Kirby, 2009).

2.1.5 Challenges in Attention and Focus

Individuals with ADHD often struggle with core attentional processes like selective, distributed, and sustained attention, which hinders their understanding of complex concepts and reasoning skills (Belmar Mellado et al., 2013). Research indicates that these attention deficits arise from difficulties in effectively engaging top-down control mechanisms, rather than from a failure to filter sensory information, especially in low-demand tasks (Friedman‐Hill et al., 2010). The impact of distractions varies, while they can hinder performance when sustained attention is low, they might actually help during high-demand tasks (Xu et al., 2004). Implementing strategies targeting specific attention-related factors, such as adjusting stimulus conditions and utilising technology, could normalise attention and enhance academic performance (Zentall, 2005; Fen & Ma, 2020; Barnett, 2017).

2.1.6 Difficulties in Task Completion

Individuals with ADHD frequently encounter difficulties initiating and completing tasks, often leading to procrastination and missed deadlines (Niermann & Scheres, 2014; Prevatt et al., 2017). These challenges are often rooted in deficits in executive functions and prospective memory (the ability to remember to carry out planned future actions), leading to forgotten appointments and deadlines (Altgassen et al., 2019; Fuermaier et al., 2013).

Motivational deficits further exacerbate these difficulties. Individuals with ADHD may exhibit reduced sensitivity to delayed rewards, making it challenging to work towards long-term goals and instead prioritising immediate gratification (Fosco et al., 2015; Furukawa et al., 2022; Oguchi et al., 2023; Bitsakou et al., 2009). This is supported by findings that ADHD symptoms strengthen the association between temporal discounting and procrastination (Oguchi et al., 2023). Interventions focusing on reward responses may therefore be beneficial. Impairments in cognitive control, particularly interference control and response selection, also contribute to difficulties in task completion (Randall et al., 2008).

2.1.7 Self-Regulation Challenges

Self-regulation, encompassing emotional and behavioural control, poses a significant challenge for individuals with ADHD, impacting academic performance and overall well-being (Burns & Martin, 2014; Welkie et al., 2020). Emotion dysregulation in ADHD can manifest as emotional impulsivity, lability, and negative emotionality, impacting social interactions and coping mechanisms (Wu et al., 2020; Decaires-Wagner, 2017). Interventions targeting both emotional and cognitive regulation are essential (González-Sánchez et al., 2019), with studies suggesting that training to enhance inhibitory control can improve ADHD symptoms (Ağayeva, 2024), and mindfulness interventions can improve emotional regulation and impulse control (Virone, 2021).

2.2 Learning Strategies for Individuals with ADHD

2.2.1 Learning for adults with ADHD

Adults with ADHD often benefit from educational strategies tailored to their experiences that facilitate connections between new information and pre-existing knowledge (Manz & Manz, 1991; Edmundson, 2008). Online courses, self-paced modules, and personalised learning paths can offer greater control and autonomy, aligning with principles of self-regulated learning (Shao-ga, 2015; Feng-cun, 2008).

However, executive function deficits common in ADHD, such as difficulties with working memory, planning, and organisation, can hinder self-directed learning despite its potential benefits (Parker & Boutelle, 2009; Sady et al., 2024; Ogrodnik et al., 2023). Consequently, structured support and guidance are often necessary. Flexible learning environments that accommodate the unique needs and preferences of adults with ADHD can foster autonomy and promote successful learning outcomes (Cornelius et al., 2009; Vemury & Devlin, 2009). This section reviews learning strategies beneficial for adults with ADHD, linking them to design considerations for ITS.

2.2.2 Motivational Deficits and Reward Structures

Individuals with ADHD often struggle with sustained motivation, leading to increased susceptibility to boredom and frustration, particularly with tasks perceived as monotonous or repetitive (Brim & Whitaker, 2000; Scime & Norvilitis, 2006). Creating stimulating, varied, and appropriately challenging learning environments, alongside support and encouragement, is crucial (Lee & Asplen, 2004; Namkoong et al., 2007; Ravichandran & Jacklyn, 2009).

Given that deficits in the dopamine reward pathway are associated with motivation deficits in adult ADHD (Volkow et al., 2010), considering motivational factors in interventions is important. Research suggests that reward-based feedback may be more effective than punishment (Morris et al., 2023). Gamification, integrating game elements like points, badges, and leaderboards into non-game contexts, can introduce fun and competition, potentially increasing participation and enhancing learning outcomes (Buckley & Doyle, 2014; Sailer et al., 2016; Rose et al., 2016). Gamified UI components and personalised feedback can further enhance motivation (Song et al., 2017). AI-powered chatbots can provide instant, tailored support (Morales et al., 2024).

However, over-reliance on external rewards can undermine intrinsic motivation if learners perceive their activity as externally controlled (Morsink et al., 2021; Shenaq, 2021; Bradley & Mannell, 1984). At the same time, some studies suggest game elements can enhance intrinsic motivation (Rodrigues et al., 2021). Therefore, gamified environments should be designed carefully. Focusing on informational feedback that increases feelings of competence and autonomy is key (Sailer et al., 2016). Badges, for example, can recognise specific achievements, providing a sense of progress (Pombo & Santos, 2023; de Almeida Souza et al., 2017).

Intrinsic motivation is fostered when material resonates with personal experiences, aligns with objectives, or sparks curiosity (Ventouri, 2020; Olivier & Steenkamp, 2003). Strategies include offering choices, nurturing autonomy, and providing opportunities for mastery (Cohen & Beattie, 1984; Kusurkar et al., 2011). Connecting learning to real-world applications is also crucial (Plaza Casado et al., 2020; Fini, 2010). While intrinsic motivation is paramount, thoughtfully designed external rewards and gamification can maintain engagement by focusing on informational feedback, promoting competence and autonomy, and tailoring rewards (Mohammed et al., 2024; Schöbel et al., 2022; Luarn et al., 2023).

2.2.3 Cognitive overload

To minimise cognitive overload for adults with ADHD, several design considerations are important for an ITS. Firstly, prioritising simplicity in interface design is crucial. A clean, uncluttered interface with limited animations and pop-ups reduces distractions and promotes focus, directing visual attention to essential information (Kusumasari et al., 2018; McCrickard &

Chewar, 2003; Zhang, 2006; McNamara et al., 2015; Carlisle, 2019; Evans et al., 2011). Consistent and intuitive navigation also supports efficient task completion (Gündogan, 2000).

Secondly, chunking information into smaller, manageable units aligns with working memory limitations and is beneficial for individuals with ADHD (Suppawittaya, 2021; Kahn et al., 1990; Carlson et al., 2003; Higgins, 2007). AI tools can automate chunking and generate simplified text tailored to individual cognitive styles (Kaur et al., 2022; Tachmazidis et al., 2020). Thirdly, clear and concise instructions are vital, as ambiguity increases cognitive load (Penningroth & Rosenberg, 1995). Cognitive remediation strategies can improve attention and organisation (Weinstein, 1994). Incorporating high perceptual load activities may also increase focus (Forster et al., 2013).

2.2.4 Active Learning

Active learning strategies, which promote engagement and deeper processing, can be particularly beneficial for adults with ADHD, leveraging their strengths like creativity and problem-solving, while traditional lecture formats can be challenging due to sustained attention difficulties (Whirley et al., 2003; Lorch et al., 2006; White & Shah, 2016). Interactive UI elements like embedded quizzes and polls can prompt immediate engagement, while clear calls-to-action guide learners (Baggaley et al., 2002; Farrow et al., 2019; Chadha, 2022).

2.2.5 Emotional regulation

Difficulties with emotional regulation are common in ADHD (Zhang & Vallabhajosyula, 2022; Zhang et al., 2020), and addressing these issues may be crucial for improving outcomes. Reward and feedback mechanisms hold significant importance, with research suggesting adults experiencing high ADHD symptom severity potentially benefiting more from reward-based feedback (Morris et al., 2023; Gabay et al., 2018). Successful AI tutoring will likely need to incorporate multiple strategies to address the diverse cognitive and emotional challenges of adult ADHD, considering its neuropsychological heterogeneity (Varrasi et al., 2022; Mostert et al., 2015).

2.3 Adaptive Learning through Intelligent Tutoring Systems

2.3.1 Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITS) are AI-driven computer systems that emulate human tutors by providing immediate, personalised instruction and feedback (Allen, 2015). They offer advantages such as personalised learning paths, potentially improved learning outcomes, and scalability (Pardosi et al., 2024; Akavova et al., 2023). AI models adapt content and pace to individual student needs, analyse data to predict areas needing help, and enable proactive intervention (Katiyar et al., 2024; Lydia et al., 2023; Luo, 2024).

AI in education extends to tools that track student behaviour, model achievements, and provide insights into progress, enabling customised lesson plans (Lydia et al., 2023; Sangheethaa & Korath, 2024). However, while promising, the effectiveness of these systems hinges on the quality of their underlying models. Traditional ITS often rely on predefined rules and models, which can be rigid and may not capture the full complexity of a learner's state, particularly for neurodivergent populations like those with ADHD (Conati & Kardan, 2013). Furthermore, challenges like data privacy, algorithmic bias, and the need for comprehensive teacher training must be addressed for ethical and effective implementation (Lydia et al., 2023; Zhu, 2024). Despite these hurdles, AI integration holds significant promise for transforming education (Katiyar et al., 2024).

2.3.2 Student Modelling

Student modelling is a core ITS component, focusing on representing a learner's knowledge, skills, learning styles, and preferences to tailor the learning experience (Conati & Kardan, 2013; Sani et al., 2016; Funk & Conlan, 2002). Effective student models consider cognitive traits, learning indicators, and affective states to create quantitative representations for adaptive environments (Hafidi & Bensebaa, 2014; Okpo et al., 2017; Hernández et al., 2004). The model hypothesises the student's current state to select appropriate teaching, assessment, and motivational strategies (Thompson, 1996; Del Soldato & du Boulay, 1995). AI and machine learning are crucial for creating student models that support personalisation (Conati & Kardan, 2013). LLMs offer new opportunities for more nuanced and dynamic student modelling by processing natural language interactions and inferring complex cognitive and affective states, as further explored in section 2.4.

2.3.3 Feedback Mechanisms

Effective learning systems incorporate feedback mechanisms to guide students (Suhailan et al., 2014). Feedback should identify errors and guide improvement (Skedsmo & Huber, 2022). In programming, automated feedback can provide correction suggestions (Suhailan et al., 2014; Král & Čápek, 2016). Real-time feedback enhances understanding and motivation (Alshahrani et al., 2017). Still, incorporating a single type of feedback mechanism limits its effectiveness across the heterogeneity of learners (Okpo et al., 2017). A system that provides only corrective feedback might increase frustration in a learner with ADHD who is already struggling, whereas a purely motivational approach may not provide enough concrete guidance (Morris et al., 2023). The challenge is to create feedback systems that balance context-awareness and emotional intelligence. Integrating feedback mechanisms into learning systems with AI models offers personalised pathways and real-time feedback, creating holistic learning experiences (Pardosi et al., 2024; Zhao et al., 2024; Erradi et al., 2023). Here, effectiveness is measured by engagement and outcomes (Haddad & Kalaani, 2020; Soelistianto et al., 2024).

2.3.4 Difficulty Adjustment & Content Adaption

Effective learning environments require dynamic difficulty adjustment to maintain student engagement and optimise outcomes, particularly for students with attention problems (Kosch et al., 2018; Reed & Martens, 2008; Sinclair et al., 1984; Tjarve-Golubeva & Rozenfelde, 2016). This involves modifying task complexity, providing scaffolding, and adapting information presentation (Kosch et al., 2018). Furthermore, content adaptation tailors the sequence and type of learning materials to match a learner's progress and learning style (Abraham-Curto, 2013). These strategies can adapt based on an ADHD symptomatic profile inferred through student modelling to personalise learning spaces (Mancera et al., 2011). The goal is to automatically adapt the educational process to each user, improving resource utilisation and scalability (Abraham-Curto, 2013; Ohene-Djan & Gorle, 2004).

However, the logic governing this adaptation is critical. Traditional rule-based adaptive systems often lack the flexibility to respond to the rapid, moment-to-moment fluctuations in attention and cognitive load characteristic of ADHD learners (Parker & Boutelle, 2009). An adaptation that is too slow or based on simplistic metrics may fail to provide the right level of support at the right time. This highlights a critical gap: the need for more dynamic, responsive systems that can interpret subtle cues from user interaction in real-time. While the principles of adaptive learning are well-established, their implementation has been constrained by the technological capabilities of older systems. The emergence of powerful LLMs presents an opportunity to overcome these limitations.

2.4 LLMs in education

2.4.1 Core Functionality of Large Language Models

Large language models present significant opportunities for developing AI-powered educational support systems, such as chatbots and virtual assistants, which provide immediate answers, guidance, and support (Kumar et al., 2024; Puertas et al., 2023). In an ITS, LLMs can facilitate customised educational experiences through detailed analysis of student performance, enabling precise and nuanced feedback and guidance that goes beyond basic error identification to include explanations tailored to individual learning styles and paces (Zainuddin & Judi, 2022; Rizvi, 2023). LLMs can also personalise question phrasing to align with student proficiency, thereby enhancing learning outcomes (Elkins et al., 2022). This section outlines core LLM functionalities relevant to ITS development, focusing on their advanced reasoning, adaptability, and natural language capabilities.

2.4.2 NLP

Natural language processing (NLP) is crucial for LLMs to effectively interact with and understand student queries, employing techniques like tokenisation, parsing, and semantic analysis to derive meaning from complex sentence structures and contextual nuances (Al-Emran & Shaalan, 2014; Swathilakshmi et al., 2021). This enables a more intuitive and organic interaction between students and ITS (Dobre, 2014). NLP techniques model individual differences from natural language input, enabling assessments of cognitive processes for more robust student models within ITS (Allen, 2015). NLP applications in education include scoring and dialogue systems providing real-time feedback and facilitating engaging interactions (Zhang & Hu, 2024; Mathew et al., 2021).

2.4.3 NLG

Next to language processing, LLMs have the capability to generate coherent, grammatically correct text in various styles, adapting to different contexts and producing human-like responses, including summaries, explanations, and creative content (Subhankar & Aniket, 2024). This technique allows for automated question generation, customised feedback, and interactive dialogue systems (Subhankar & Aniket, 2024). However, challenges remain in ensuring pedagogical accuracy, mitigating biases, and maintaining engagement (Subhankar & Aniket, 2024).

2.5 Literature Gaps & Study Contributions

2.5.1 Identified Literature Gaps

Interventions that focus on self-regulation and executive function show promise for improving learning outcomes for adults with ADHD (Knouse et al., 2011; Tzuriel et al., 2017). AI-driven personalised learning can tailor educational content to address weaknesses and promote success, including personalised recommendations and lesson plans (Sugiarso et al., 2024; Gupta, 2024; Bressane et al., 2023; Sangheethaa & Korath, 2024; van der Vorst & Jelicic, 2019). However, careful integration is necessary to avoid intensifying symptoms and to support critical thinking, which requires consideration of ethical and practical limitations (Salameh, 2024; Santos et al., 2024).

The application of LLMs within adaptive tutoring systems for learners with ADHD is an underexplored area. While research exists on AI interventions for ADHD (Parker et al., 2011; Parker & Boutelle, 2009) and LLMs in education (Noguera et al., 2017), studies at their intersection, specifically for this demographic, are limited. LLMs have shown significant potential in educational settings, offering personalised feedback and content generation (Kumar et al., 2024; Noguera et al., 2017). Kumar et al. (2024) explore LLMs in supported learning environments, noting effects on interaction dynamics, learner performance, confidence, and trust. Their study, however, is not specific to ADHD learners. Noguera et al. (2017) propose a web-based adaptive ITS, yet it predates widespread LLM use and does not address ADHD-specific adaptations. A similar study creating an ITS for ADHD learners features physical systems like face recognition (Thawalampola et al., 2024), while it also focuses on content adaptation and break recommendations, rather than engagement and cognitive loads. A text-based solution does not exist. Current adaptive systems often lack the dynamic, real-time responsiveness needed to accommodate the fluctuating attention, motivation, and cognitive load experienced by ADHD learners (Parker & Boutelle, 2009).

The gap is significant, as college students with ADHD face distinct challenges in executive functioning, self-regulation, and academic performance (Slamka et al., 2021; Richman et al., 2014). LLMs' potential to personalise learning, provide tailored feedback, and offer on-demand support could address these challenges (Liu et al., 2024; Noguera et al., 2017). Still, further research is needed to evaluate LLM effectiveness in this context and identify implementation best practices, potentially leading to more effective support systems and improved outcomes (Willoughby & Evans, 2019).

2.5.2 Study Contributions

This study bridges the gaps in adaptive learning for adults with ADHD by introducing an LLM-powered adaptive Intelligent Tutoring System (ITS) that employs real-time, trait-based adaptations.

Given that learners with ADHD face challenges with fluctuating attention, motivation, and cognitive load (Parker & Boutelle, 2009; Kusumasari et al., 2018), this research investigates if an LLM-powered adaptive Intelligent Tutoring System (ITS) that employs real-time, trait-based adaptations can improve trait profiles and reduce this cognitive strain. By personalising feedback and interaction style, the ITS aims to address the motivational deficits associated with ADHD's dopamine reward pathway dysfunctions (Volkow et al., 2010). While the literature suggests adaptive systems can influence a user's internal state, these systems do not yet utilise the adaptive power of newer LLMs, and it is unclear if these benefits translate to better outcomes (Kumar et al., 2024; Conati & Kardan, 2013). Therefore, this study also examines if these real-time adaptations lead to higher user satisfaction and improved learning performance, an area where LLM effectiveness for this demographic is yet to be established (Kumar et al., 2024). Furthermore, by focusing on a text-only system, this study deviates from physical monitoring systems (Thawalampola et al., 2024) and leverages LLMs' advanced language capabilities to create a more scalable and accessible tool for ADHD learners. Given that no single symptom is uniquely diagnostic of ADHD (Arnold, 2011), the AI tutor developed in this research is not intended for diagnostic purposes. Instead, it focuses on supporting specific learning and executive function skills, complementing but never replacing professional clinical evaluation and treatment.

Based on the literature review, the following research questions can be formulated:

1. Do the real-time trait scores (e.g., engagement, frustration) of learners with ADHD show more favourable patterns when interacting with an adaptive ITS compared to a non-adaptive ITS?
2. Do learners with ADHD report higher user satisfaction when using an adaptive ITS compared to a non-adaptive ITS?
3. Do learners with ADHD experience lower cognitive load when using an adaptive ITS compared to a non-adaptive ITS?
4. Does an adaptive ITS lead to improved learning performance in Swahili vocabulary and grammar for learners with ADHD compared to a non-adaptive ITS?

3 Experiment Methodology

3.1 Introduction

This chapter outlines the methodology for evaluating the Intelligent Tutoring System. The evaluation adopts a design study approach and is guided by the following research questions:

1. Do the real-time trait scores (e.g., engagement, frustration) of learners with ADHD show more favourable patterns when interacting with an adaptive ITS compared to a non-adaptive ITS?
2. Do learners with ADHD report higher user satisfaction when using an adaptive ITS compared to a non-adaptive ITS?
3. Do learners with ADHD experience lower cognitive load when using an adaptive ITS compared to a non-adaptive ITS?
4. Does an adaptive ITS lead to improved learning performance in Swahili vocabulary and grammar for learners with ADHD compared to a non-adaptive ITS?

This chapter further dives into the methodology used to evaluate the ITS, outlining its systematic approach to address the research questions.

3.2 Research Design

The study employs a between-subjects A/B testing design to evaluate Jabari's adaptive features for adults with ADHD. Two independent groups are compared: one group uses the adaptive Jabari ITS, which tailors responses based on real-time trait analysis (as detailed in section 4.4), while the other group uses a non-adaptive version, delivering identical Swahili content without trait-based adaptations in interaction style and instructional approach, essentially creating a static progression of the word set. Both groups' interactions, including trait scores, are logged, but only the adaptive group's data is used for personalisation.

3.3 Participants

The target population for this study consists of adults with a confirmed diagnosis of ADHD. Participants must have sufficient English proficiency to engage with the study's instructions, while they must have no prior knowledge of Swahili. The targeted study size is 60 participants to ensure statistical significance.

Recruitment will be conducted through Prolific, to ensure a significant number of participants is reached. Prolific is an online platform where researchers can find research participants in exchange for a small monetary incentive. Recruitment instructions will outline the study's purpose and duration, as well as emphasising anonymity and voluntary participation.

3.4 Data Collection

This study uses a quantitative data collection method to evaluate the four hypotheses linked to this research. Exclusively primary data will be collected. All data will be collected during the online experiment on the web application and stored in a Google Firestore Database in real-time. Participants generate an anonymous userID upon logging into the web application, which secures the anonymity of user data. There are several data points to be collected during the experiment.

First of all, the running average of nine different personality traits, further outlined in section 4, is continuously updated in the database. This allows for real-time state management during the experiment. After a user logs off the application, the average trait scores are saved, which directly correlates to the first research question: “Do the real-time trait scores (e.g., engagement, frustration) of learners with ADHD show more favourable patterns when interacting with an adaptive ITS compared to a non-adaptive ITS?”. As further elaborated in section 4, trait scores will have a value between 0 and 10. However, not all nine traits follow the same reasoning logic with their scores. Three traits, namely confidence, engagement, and motivation, are positive indicators that follow maximisation objectives. The other six trait averages are negative indicators that follow minimisation objectives. Lower scores in these traits are considered favourable. Along with the trait averages, a count of the number of trait updates is tracked, which directly correlates with the number of interactions a user has with Jabari during the experiment.

Secondly, after the learning phase is completed, the participants are prompted to continue with a questionnaire, in which three different sections are presented. The first section contains a handful of personal questions related to basic personal information, such as age and nationality, as well as confirming their diagnoses of ADHD.

The second section of this questionnaire is directly related to the second research question: “Do learners with ADHD report higher user satisfaction when using an adaptive ITS compared to a non-adaptive ITS?”. User satisfaction is measured with the Likert scale (Likert, 1932), a 5-point scale that assesses ease of use, helpfulness, engagement, focus, motivation and pace. All scales are positive indicators, with a higher score deemed more favourable.

The third section of the questionnaire is directly linked to the third research question: “Do learners with ADHD experience lower cognitive load when using an adaptive ITS compared to a non-adaptive ITS?”. Cognitive load is measured by a NASA Task Load Index (NASA-TLX), a validated tool that measures cognitive load across six scales: mental demand, physical demand, temporal demand, performance, effort, and frustration. (Hart & Staveland, 1988). In this instance, the performance scale serves as the sole positive indicator, with a higher score deemed more favourable. In contrast, the other scales act as negative indicators, where a lower score is regarded as preferable.

Lastly, the fourth research question: “Does an adaptive ITS lead to improved learning performance in Swahili vocabulary and grammar for learners with ADHD compared to a non-adaptive ITS?” is assessed at the end of the experiment using a pre-set Swahili knowledge test, which consists of multiple-choice and open questions that measure Swahili language retention after the learning session. The test is identical for each participant.

The complete list of questions for the questionnaire and the Swahili test can be found in Appendices F and G.

3.5 Experimental Procedure

The experiment follows a structured, online procedure. Participants access the study via a provided link, generate a unique, anonymised username, and review the home page of the application featuring the instructions, purpose and procedure of the study. Digital informed consent is obtained, ensuring ethical compliance (Yusof et al., 2022). Automatically split by the generated usernames, 50% of participants are assigned to the experimental group, and 50% to the control group.

The participants engage with their assigned Jabari version for 25 minutes, whereafter they fill in the questionnaires and the Swahili test, as detailed in section 3.4. After finishing the questionnaires, the participants are notified that the experiment has been completed and logging off is safe.

The total duration of the procedure slightly varies for participants, but its average duration is aimed to be 40 minutes.

3.6 Dependent Variables and Measures

The study evaluates the effectiveness of the ITS through four dependent variables, each linked to a research question. Firstly, user trait profiles are measured on nine different traits. As aforementioned, three traits are positive indicators, while six traits are negative indicators. To measure and compare, the negative indicators are inverted, resulting in equal score indicators for all traits. An average score across the nine traits will quantify favourable patterns in trait scores to assess the hypothesis. Second, user satisfaction is measured through the Likert scale, with 6 scales being measured on 5 points (Strongly Disagree = 1 to Strongly Agree =5). An average score across scales quantifies satisfaction per participant. Thirdly, cognitive load is assessed using the NASA-TLX, with scores ranging from 0 to 100 in 6 different scales. Similar to the inverted trait score, the scale measuring performance will be inverted, as it represents the only positive indicator in an index with merely negative indicators. An average score across scales quantifies perceived cognitive load per participant. Lastly, learning performance is measured through the number of correct answers to the Swahili test questions. Answers to the questions are considered to be either correct or incorrect.

3.7 Hypotheses

The specific hypotheses, aligned with the four research questions, are as follows:

H1 (Trait Profiles): Learners with ADHD using the adaptive ITS will exhibit more favourable trait score patterns compared to those using the non-adaptive ITS.

H2 (User Satisfaction): Learners with ADHD using the adaptive ITS will report significantly higher user satisfaction scores on the 5-point Likert scale compared to those using the non-adaptive ITS.

H3 (Cognitive Load): Learners with ADHD using the adaptive ITS will report significantly lower cognitive load scores on the NASA-TLX compared to those using the non-adaptive ITS.

H4 (Learning Performance): Learners with ADHD using the adaptive ITS will show significantly greater improvement in Swahili vocabulary and grammar test scores compared to those using the non-adaptive ITS.

3.8 Data Analysis Plan

The study employs quantitative statistical analysis within an A/B testing framework. Firstly, descriptive statistics will be calculated for demographic variables, trait scores, Likert scale scores, NASA-TLX scores, and test scores.

Afterwards, normality (Shapiro-Wilk test) and homogeneity of variance (Levene's test) will be checked using scipy.stats. If no normality or homogeneity assumptions are violated (at $p < 0.05$), each of the four hypotheses will be tested with independent t-tests that will compare mean scores for each of the dependent variables. If either normality or homogeneity assumptions are violated, the Mann-Whitney U test is applied as a non-parametric alternative, as it does not require normal distributions or equal variances and is suitable for comparing independent groups in A/B testing.

Significance level: All tests will use an alpha level of $p < 0.05$.

3.9 Ethical Considerations

The study adheres to ethical guidelines to ensure participant safety, anonymity, and confidentiality, in line with ethics principles set out by RUG (RUG, 2025). The author of this research is the sole researcher, and participant data will not be shared with anybody else. More key considerations include:

- Informed consent: Participants receive information outlining the study's purpose, procedures, duration, and their right to withdraw at any time.
- Pseudonymisation: Upon entering the experiment, participants generate pseudonymised usernames, ensuring direct personal identifiers are not collected, and no individual data points can be linked to specific participants in the experiment.
- Encryption: The data collected is stored in Google's Firestore, a cloud database service, which automatically encrypts data when stored in the cloud (Google, 2025).

4 System Design

4.1 Introduction

This chapter details the design and implementation of "Jabari," an adaptive Intelligent Tutoring System (ITS) central to this Design Study. Jabari serves as a Swahili tutor tailored for adults with ADHD, guiding them through a structured learning experiment. It guides users through a structured learning phase of 25 minutes via a chat-based interface. It is programmed to be encouraging, supportive, and human-like. Its core function is to teach basic Swahili vocabulary and grammar across four levels, adapting instructions and feedback based on real-time trait analysis of nine ADHD-relevant traits, including inattention, frustration, and motivation, designed specifically for the heterogeneity of ADHD learners. For example, if frustration is high, it will simplify instructions and offer encouraging feedback. Else, if engagement is low, it prompts the learners to re-engage by asking a follow-up question. This functionality is powered by an LLM, specifically Google's Gemini 2.0 Flash, which powers the adaptive engine that is built into Jabari. A full outline of the system's technical architecture can be found in Appendix A. This chapter will outline the design goals, system architecture, the mechanics of its adaptive engine, and key interface considerations for the development of Jabari.

4.2 Design Goals and Rationale

The primary design goal for Jabari was to create an ITS that directly addresses the known learning challenges faced by adults with ADHD, as identified in the literature review. These challenges include difficulties with sustained attention (Salomone et al., 2016), task initiation and completion (Niermann & Scheres, 2014), motivation (Volkow et al., 2010), and potential cognitive overload (Kusumasari et al., 2018). The rationale behind Jabari's adaptive features is rooted in learning strategies proven beneficial for ADHD learners, such as:

- **Minimising Cognitive Load:** Achieved through clear, chunked information presentation, simple UI, and adaptive simplification of instructions when traits like fatigue or frustration are high.
- **Enhancing Motivation and Engagement:** Implemented via personalised feedback, adaptive difficulty, and responses tailored to user interest levels (inferred from engagement scores).
- **Supporting Executive Functions:** Facilitated by structured learning levels, clear progress indicators, and adaptive guidance that can break down tasks or reframe instructions based on user performance and trait analysis.
- **Providing Personalised Support:** Realised through the core adaptive engine that tailors interactions based on a nuanced understanding of the user's current cognitive and emotional state.

Jabari was, therefore, conceived not just as a language tutor but as a tutor sensitive to the unique and heterogeneous needs of ADHD learners.

4.3 Trait Calculation

The foundation in Jabari's adaptability lies in its continuous evaluation of nine traits critical to understanding the learning experience:

1. **Inattention** is a core symptom of ADHD and a significant barrier to learning. Research by Salomone et al. (2016) demonstrates that adults with ADHD exhibit substantial attentional impairments, making it challenging to maintain focus on educational tasks.
2. **Frustration** often arises from emotional dysregulation, a common issue in ADHD. Shaw et al. (2014) note that individuals with ADHD frequently struggle with managing emotions, which can disrupt learning when tasks become challenging.
3. **Confidence**, tied to self-efficacy, is essential for motivation and task persistence. Knouse et al. (2011) explore how self-regulation difficulties in ADHD can undermine confidence, impacting learning outcomes.
4. **Sloppiness,** often manifesting as disorganised or careless work, is a significant trait in ADHD learners. Barkley (2015) highlights that difficulties with executive functioning lead to errors in tasks that require precision.
5. **Engagement** is vital for effective learning, particularly for individuals with ADHD who may struggle to stay involved. Sailer et al. (2016) highlight how personalised strategies can enhance engagement, making it a critical trait for Jabari to monitor and optimise.
6. **Boredom** is linked to motivational deficits in ADHD. Volkow et al. (2010) suggest that reward processing differences in ADHD can lead to boredom during unstimulating tasks.
7. **Motivation** drives learning success, yet adults with ADHD often face challenges with intrinsic motivation due to neurological differences (Morsink et al., 2021).
8. **Impulsivity**, another hallmark of ADHD, can lead to rushed or off-task behaviour during learning (Fernandes Malloy-Diniz et al., 2007).
9. **Fatigue**, tied to cognitive overload, is a significant concern for individuals with ADHD, who may struggle with sustained mental effort (Kusumasari et al., 2018).

While interacting with Jabari, each of these nine traits is assigned a score between 0 and 10, updating after every interaction. The scoring process combines two parallel approaches: quantitative metric analysis and AI-powered sentiment analysis. A set of off-topic questions is also introduced, impacting the final weighted scores.

4.3.1 Quantitative Metric Analysis

Quantitative metrics provide an objective measure of user behaviour during interactions. Jabari tracks the following data points:

- **Word Count**: The number of words in the user's response.
- **Response Time**: The time taken to submit a response.
- **Correctness**: A yes/no indicator of whether the response answers a question correctly.
- **Relevance**: A score (0–1) estimating how closely the response aligns with the current learning topic.
- **Consecutive**: The number of consecutive correct or incorrect answers.

- **Off-topic**: A yes/no flag for responses unrelated to the task.
- **Typos**: The count of spelling errors in the response.
- **Attempts**: The number of tries taken for a specific word or concept.
- **Session** Duration: The total time spent in the current session.

Pre-defined formulas use these metrics to calculate a quantitative score for each of the nine traits. In designing the formulas, specific choices were informed by the literature on ADHD symptoms and behaviour. For instance, in the Inattention trait formula, off-topic responses are heavily penalised, supported by research indicating that individuals with ADHD are prone to distraction and have difficulty maintaining focus on tasks (Forster et al., 2013; Friedman-Hill et al., 2010). Similarly, for the Impulsivity trait, very short response times are associated with higher scores, reflecting the characteristic of acting quickly without sufficient deliberation (Malloy-Diniz et al., 2007). The presence of typos contributes to both Inattention and Impulsivity scores, aligning with the understanding that careless errors are common in ADHD due to both attentional lapses and hasty responses (Barkley, 2015). Furthermore, the Frustration trait formula incorporates factors such as multiple attempts and consecutive incorrect answers, which are likely to induce frustration, a common emotional response in ADHD individuals when faced with challenging tasks Shaw et al., 2014. In the Confidence trait formula, consecutive correct answers significantly boost the score, reflecting the positive impact of success on self-efficacy. Research shows that positive reinforcement and achievement recognition can enhance motivation and confidence in learners with ADHD (Ventouri, 2020; Sailer et al., 2017). These literature-backed choices ensure that the trait scoring system accurately reflects commonly found ADHD behaviours, enabling adaptation based on the specific needs of ADHD learners. The full list of trait formulas can be found in Appendix B.

4.3.2 AI-Powered Sentiment Analysis

In addition to the quantitative analysis, the user’s input is analysed using the Gemini API. This method, parallel to the quantitative analysis, leverages the Natural Language Processing of Gemini to analyse the trait scores and provide a more comprehensive assessment of the user input.

4.3.3 Off-Topic Engagement Prompts

To gather richer data for trait analysis, especially for traits less apparent in short, task-focused Swahili answers, Jabari introduces an "off-topic" question every 12 interactions. These questions are designed to encourage slightly longer, more expressive free-text responses. Examples include:

- 'What was your last holiday location? Tell me a bit about it.'
- 'Describe a favourite hobby or activity you enjoy.'
- 'What’s a book or movie you recently enjoyed? Why?'

The off-topic questions have two distinct functions. Firstly, open-ended questions foster engagement and deeper expression in learners with ADHD (Whirley et al., 2003). Whirley et al.

highlight how interactive tasks improve cognitive engagement in ADHD individuals, suggesting that varied prompts can sustain interest. Secondly, open-ended questions prompt users to express themselves further, as well as probing questions that have a different type of answer, enabling a more varied assessment of the user input, which stimulates a more complete trait analysis. In general, longer prompts are shown to be beneficial to LLMs as they provide more knowledge (Liu et al., 2025). The trait scores derived from the user's response to these off-topic questions are weighted three times more heavily in the subsequent trait score update, reflecting the richer information they provide. After the user responds, Jabari transitions back to the Swahili learning content. The full list of Off-Topic Engagement Prompts can be found in Appendix C.

4.3.4 Score integration

For the final trait scores, both processes are collected, and a single final trait score is calculated using a weighted average. The final trait score considers 60% of the quantitative score and 40% of the AI score. The 60% weight on quantitative scores reflects their reliability as objective measures, while the 40% weight on AI scores incorporates the nuanced insights from sentiment analysis. Final scores are capped between 0 and 10, and Jabari maintains a running average for each trait, updated after every interaction. This approach ensures that adaptations are based on longer-term trends.

4.4 Adaptive Prompt Generation

Jabari's responses are generated through a multi-prompt approach, particularly in the adaptive version. After each interaction, instructions are constructed with a pre-set prompt framework, varying its response based on the trait scores and the current state of the experiment (e.g. which word is taught next). 3 prompt levels can be identified in the full prompt:

1. **Base Prompt:** A foundational prompt defines Jabari's core personality and instructional style.
2. **Experiment State Guidance (Static Component):** A static part of the prompt logic ensures the user is guided systematically through the four learning levels. It manages progression, introduces new words/concepts, and poses questions to check understanding. Its sole purpose is to guide the user through the experiment, making sure each word and level is taught. The prompt logic is written generically and does not take into account the ADHD-specific design goals set out. This component is active in both experimental and control versions of the experiment.
3. **Trait-Based Adaptation/Specific Guidance (Dynamic Component - Experimental Group Only):** Key considerations for ADHD learners are found in the Specific Guidance component of the prompt generation. Here, several additional instructions related to the literature are included, along with the feature that highlights the key difference between the functionality of the experimental group and the control group. Here, the system dynamically modifies its prompts based on the continuously updated trait scores. After each user interaction, the system identifies which trait scores have changed most

significantly. The system then selects these traits, and their specific scores represent an addition to the prompt that is sent for the next interaction generation. Trait scores are divided into five thresholds: 0-2 = minimal, 2-4 = low, 4-6 = moderate, 6-8 = high, 8-10 = very high. For each trait and each threshold, specific additions to the prompt are defined and added. For example, when a user's most changed trait is identified as motivation, and its corresponding score at that time is 3.4 (low), the following instructions are added:

- *"Set very small, easily achievable goals to build momentum."*
- *"Use frequent, tangible praise for effort and completion."*
- *"Break tasks down to reduce perceived effort."*
- *"Gently remind them of the benefits or relevance of learning."*

Below, one representative prompt instruction per trait is provided to demonstrate the adaptive mechanism of the system:

Inattention: At a high threshold (6–8), Jabari is instructed to "reduce content to only essential information" and use engaging prompts to recapture focus. This aligns with Salomone et al. (2016) and Zentall (2005), who emphasise minimising distractions and enhancing engagement to support attention in ADHD learners.

Frustration: For a moderate threshold (4–6), the system is instructed to "Reinforce progress with a positive comment" and breaks tasks into smaller steps. Shaw et al. (2014) and González-Sánchez et al. (2019) highlight the value of emotional support and task simplification to reduce frustration.

Confidence: When confidence is low (2–4), Jabari is directed to "emphasise effort with tangible, positive feedback" and ensure small, successful steps. Knouse et al. (2011) and Morris et al. (2023) underscore positive reinforcement as critical for building self-efficacy in ADHD individuals.

Sloppiness: At a minimal threshold (0–2), the system provides "clear, structured instructions to promote accuracy" with examples for clarity. Barkley (2015) and Knouse et al. (2011) note that structured guidance mitigates executive function deficits, reducing errors.

Engagement: For a low threshold (2–4), Jabari "Ask a question that connects to real-world applications", to sustain interest. Sailer et al. (2016) and Plaza Casado et al. (2020) advocate for interactive tasks to maintain engagement in learning contexts.

Boredom: At a high threshold (6–8), the system "Asks a question that encourages creative or personal input". Volkow et al. (2010) and Plaza Casado et al. (2020) stress the need for stimulation to address motivational deficits in ADHD.

Motivation: When motivation is very high (8–10), Jabari "offers challenging tasks to leverage high motivation" with enthusiastic feedback. Volkow et al. (2010) and Sailer et al. (2016) suggest aligning task difficulty with motivation to optimise engagement.

Impulsivity: For a moderate threshold (4–6), the system "encourages a pause before responding to questions" to promote deliberation. Fernandes Malloy-Diniz et al. (2007) and Barkley (2015) recommend strategies to slow impulsive responses in ADHD learners.

Fatigue: At a high threshold (6–8), Jabari "limits tasks to essential, low-effort activities". Kusumasari et al. (2018) and Knouse et al. (2011) emphasise reducing cognitive load and incorporating rest to manage fatigue.

The full configuration of trait thresholds and corresponding prompt additions is detailed in Appendix D.

The full configuration of the prompt set-up through its different levels can be found in Appendix E.

4.5 User Interface (UI) and User Experience (UX) Design

Jabari's UI/UX design prioritises creating a supportive learning environment for adults with ADHD, addressing their challenges with attention, cognitive load, and motivation. It incorporates several considerations to enhance usability for ADHD learners. Firstly, simplicity and clarity: The chat-based interface is minimalist, with an uncluttered layout to minimise distractions, aligning with research on reducing cognitive overload for ADHD learners (Kusumasari et al., 2018). Straightforward typography and high-contrast colours ensure readability. Next to this, visual cues are emphasised with bold or italic formatting, aiding comprehension and focus (Carlson et al., 2003). Progress indicators, such as “Level 2 of 4”, provide a sense of achievement and structure, supporting executive functioning (Knouse et al., 2011). Furthermore, a visible 25-minute session timer helps users manage their focus, addressing time perception difficulties common in ADHD (Barkley, 1997). All in all, these UI/UX elements are considered to create a distraction-free environment that supports sustained learning for learners with ADHD.

5 Results

This chapter presents the findings of the statistical analysis conducted. Data from 64 participants, with 34 in the control group and 30 in the experiment group, was cleaned to make sure participant criteria were met. Afterwards, data was analysed using a Python script that produced descriptive statistics, normality and homogeneity tests, and hypothesis tests performed at a significance level of $\alpha = 0.05$.

5.1 Data cleaning

Before statistical analysis was performed, the questionnaires were checked to see if participant criteria were met. Out of the 64 participants, 6 participants fulfilled the experiment, but were identified without the diagnosis of ADHD. Another 2 participants marked Swahili as (one of) their spoken language(s). The 8 participants were removed from the data to maintain the study's focus as outlined in section 3.3, leaving a participant pool of 56 participants, with 30 in the control group and 26 in the experimental group. Furthermore, the trait scores that were identified as negative indicators in section 4.4 were inverted to ensure rigid comparisons of mean scores. Furthermore, the NASA-TLX scale for performance was inverted, as this was the sole positive indicator for this scale, as detailed in section 3.4.

5.2 Descriptive Statistics

Before presenting the statistical results, some general descriptive statistics can be outlined. The following tables outline the frequency counts for the demographic variables of nationality, highest education level obtained and ADHD type:

Nationality → Group ↓	**African**	**British**	**Nigerian**	**Portuguese**	**South-African**	**American**
Control	1	3	0	0	10	16
Experimental	0	3	1	1	4	17

Group → Education ↓	**Control**	**Experiment**
High School	0	2
Vocational	1	1
Bachelor	15	12
Master	8	7
Doctoral	6	4

Group → ADHD Type ↓	**Control**	**Experiment**
Hyperactive / Impulsive	12	8
Inattentive	4	5
Combined	12	11
Not sure	0	1
Prefer not to say	2	1

Figure 5.1: Frequency counts for nationality, educational level, and ADHD subtype

Descriptive statistics for the four dependent variables are summarised in Figure 5.2, which presents means and standard deviations for age and the four dependent variables for the control and experimental groups.

Variable	Group	Mean	Standard Deviation
Age	Control	36.10	11.71
	Experimental	31.23	12.20
Trait Profile	Control	4.37	0.56
	Experimental	5.79	0.78
User Satisfaction	Control	3.42	3.42
	Experimental	4.04	0.65
Cognitive Load	Control	56.89	17.55
	Experimental	48.37	17.34
Right Test Answers	Control	10.83	3.14
	Experimental	11.35	2.83

Figure 5.2: Mean and Standard Deviation scores of age and dependent variables

The trait profile, an average of nine trait indicators (with negative traits inverted as described in Section 4.6), shows a notably higher mean in the experimental group (5.79) compared to the control group (4.37), suggesting more favourable trait patterns with the adaptive ITS. User satisfaction also reveals a higher mean in the experimental group (4.04) than in the control group (3.42), though the control group exhibits greater variability (SD = 1.41 vs. SD = 0.65). Cognitive load indicates a lower mean score in the experimental group (48.37) compared to the control group (56.89), hinting at reduced cognitive demand with the adaptive system. Finally, learning performance, reflected by the number of correct Swahili test answers, shows a slightly higher mean in the experimental group (11.35) than in the control group (10.83).

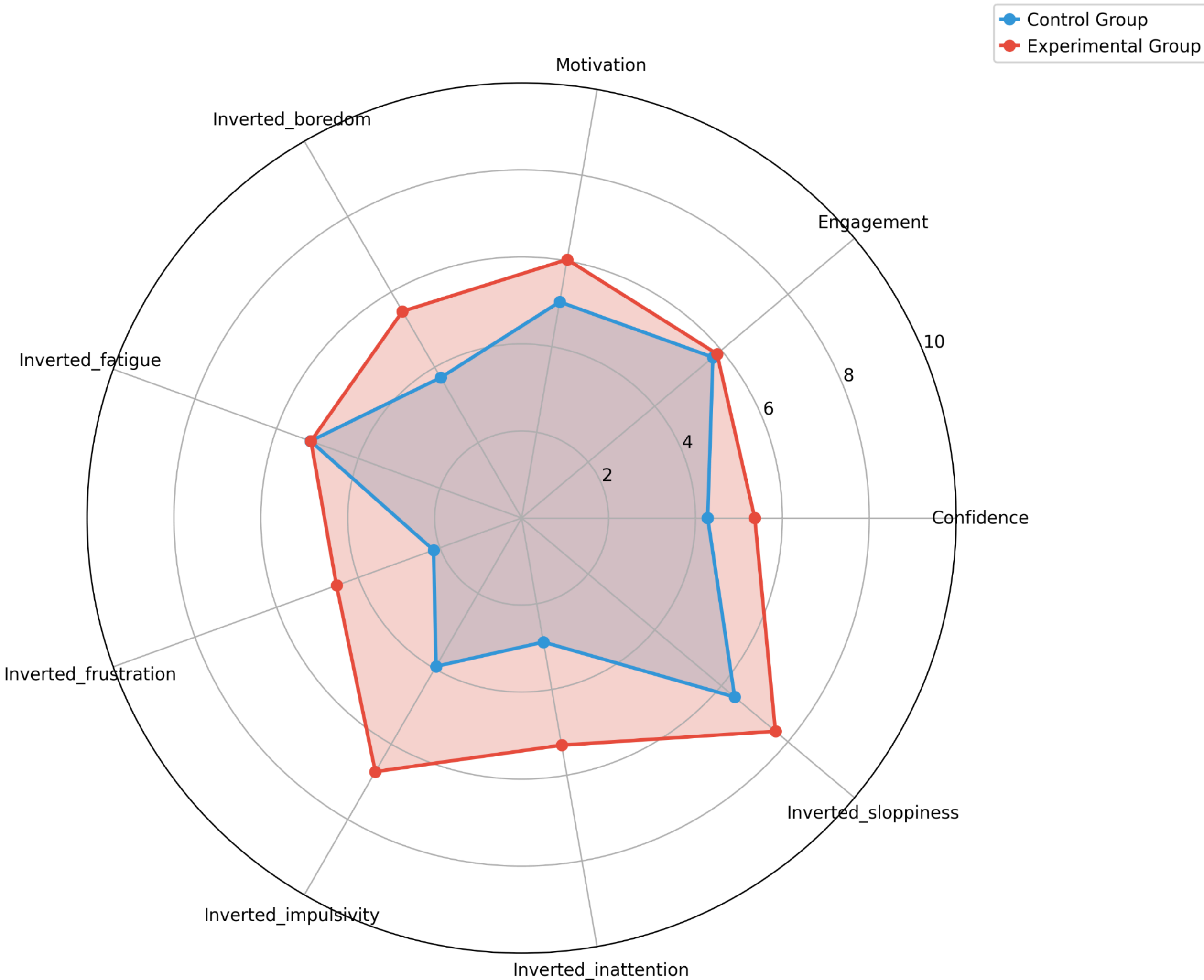


Figure 5.3: Mean scores per trait in both groups

As illustrated by Figure 5.3, the experimental group demonstrated a more favourable trait profile across nearly all measures. The most significant improvements were in reduced frustration, impulsivity, and inattention, along with substantial gains in confidence and motivation. In contrast, engagement levels were only slightly higher, while fatigue scores remained virtually identical between the two groups.

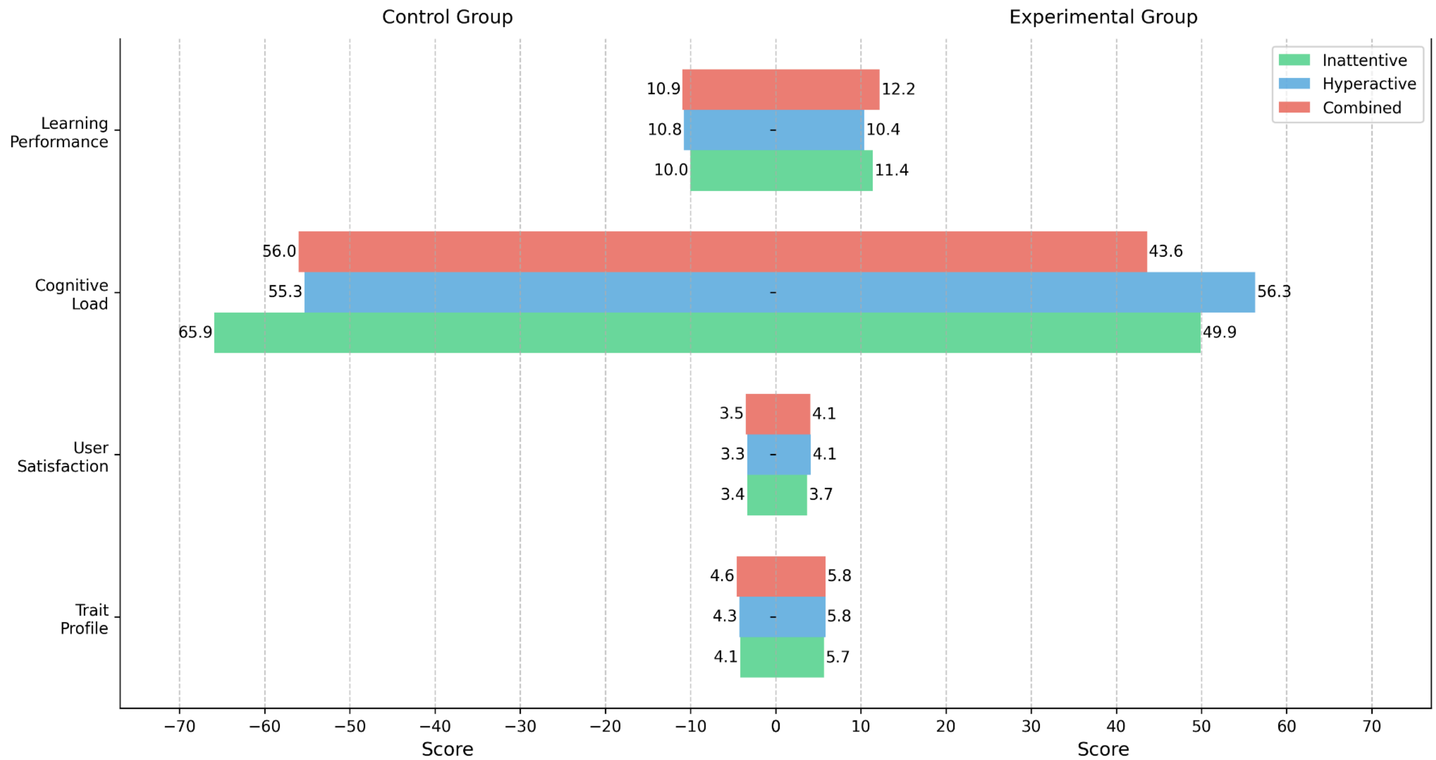


Figure 5.4: Dependent variables means sorted by ADHD subtype

The dependent variables were analysed across the three main ADHD subtypes, namely the predominantly Hyperactive/Impulsive type (ADHD), the predominantly Inattentive type (ADD), and the combined type. Figure 5.4 shows the comparison of means for both the experimental and control groups. For the dependent variables of learning performance, user satisfaction, and trait profile, no large variance was found. However, the perceived cognitive load scores show a significant difference in scores across the different ADHD subtypes. Moreover, it shows that for the Hyperactive/Impulsive subtype, the cognitive load in the experimental group was even higher than the control group. For the combined subtype, and especially the Inattentive subtype, Jabari showed a significant decrease in perceived cognitive load.

5.3 Normality and Homogeneity Tests

To determine the appropriate statistical tests, normality of the dependent variables was assessed using the Shapiro-Wilk test, and homogeneity of variance was evaluated with Levene's test. The results, presented in Figure 5.5, informed the choice between parametric (independent t-test) and non-parametric (Mann-Whitney U) tests as outlined in section 4.8.

Variable	Shapiro-Wilk (Control)	Shapiro-Wilk (Experimental)	Levene's Test
Trait Profile	p = 0.888	p = 0.076	p = 0.181
User Satisfaction	p = 0.002	p = 0.043	p = 0.001
Cognitive Load	p = 0.227	p = 0.210	p = 0.902
Right Test Answers	p = 0.000	p = 0.002	p = 0.685

Figure 5.5: Normality and Homogeneity scores of the dependent variables

For the trait profile, both groups satisfied the normality assumption ($p > 0.05$), and Levene's test confirmed homogeneity of variance ($p = 0.181$). Thus, an independent t-test was deemed appropriate for testing H1

User satisfaction test scores violated normality in both groups ($p < 0.05$) and showed unequal variances ($p = 0.001$), necessitating the Mann-Whitney U test for H2.

Cognitive load met the normality assumption ($p > 0.05$) and exhibited homogeneous variances ($p = 0.902$), making the independent t-test suitable for H3.

Finally, learning performance (right test answers) failed the normality test in both groups ($p < 0.05$), though variances were equal ($p = 0.685$). As a result, the Mann-Whitney U test was selected for H4.

The Q-Q plots in Appendix H visually assess the normality of the dependent variables (trait profile, user satisfaction, cognitive load, and right test answers) for the Control and Experimental groups. Data points closely align with the red reference line for the variables of trait profiles and cognitive load, indicating approximate normality. For user satisfaction and right test answers, deviations suggest non-normality, consistent with Shapiro-Wilk results (Figure 5.5).

5.4 Statistical Tests

The statistical tests conducted for each hypothesis are summarised in Figure 5.6, detailing the test type, statistic, and p-value. The following subsections elaborate on these findings, interpreting the results in the context of the null (H0) and alternative (H1) hypotheses defined in Section 4.7.

Hypothesis	Variable	Test Type	Test statistic	P-Value
H1	Trait Profile	Independent t-test	t = 7.863	p < 0.001
H2	User Satisfaction	Mann-Whitney U	U = 442.500	p = 0.195
H3	Cognitive Load	Independent t-test	t = -1.823	p = 0.037
H4	Right Test Answers	Mann-Whitney U	U = 433.000	p = 0.239

Figure 5.6: Test Statistics

5.4.1 H1: Trait Profiles

The null hypothesis (H0) for H1 assumes that there is no difference in trait score patterns between the learners with ADHD using the adaptive ITS and those using the non-adaptive ITS. The alternative hypothesis (H1) proposed that learners with ADHD using the adaptive ITS would exhibit more favourable trait score patterns. An independent t-test revealed a significant difference ($t = 7.863$, $p < 0.001$) between the control group and the experimental group. Thus, H1 is supported, which is in line with the higher mean trait profile scores in the experimental group (5.79 vs 4.37).

5.4.1 H2: User Satisfaction

The null hypothesis (H0) for H1 assumes that there is no difference in reported user satisfaction scores between the learners with ADHD using the adaptive ITS and those using the non-adaptive ITS. The alternative hypothesis (H1) proposed that learners with ADHD using the adaptive ITS would report higher user satisfaction scores. A Mann-Whitney U test was conducted, resulting in a statistic of $U = 442.500$ and a p-value of 0.195, which is above the significance threshold of $\alpha = 0.05$. As a result, H0 cannot be rejected, suggesting no significant statistical difference in user satisfaction between the groups

5.4.1 H3: Cognitive Load

The null hypothesis (H0) for H1 assumes that there is no difference in perceived cognitive load scores between the learners with ADHD using the adaptive ITS and those using the non-adaptive ITS. The alternative hypothesis (H1) proposed that learners with ADHD using the adaptive ITS would report lower perceived cognitive load scores. An independent t-test revealed a significant difference ($t = -1.823$, $p = 0.037$) between the control group and the experimental group. Thus, H1 is supported. This is in line with the experimental group’s lower mean cognitive load score (48.37) compared to the control group (56.89).

5.4.1 H4: Learning Performance

The null hypothesis (H0) for H1 assumes that there is no difference in Swahili vocabulary test scores between the learners with ADHD using the adaptive ITS and those using the non-adaptive ITS. The alternative hypothesis (H1) proposed that learners with ADHD using the adaptive ITS would perform better in the final test. A Mann-Whitney U-test was performed, resulting in a statistic of $U = 433.000$ and a p-value of 0.239, exceeding the threshold significance level of $\alpha = 0.05$. Therefore, H0 cannot be rejected, suggesting no significant difference in learning performance between the groups.

6 Discussion

6.1 Conclusion

The statistical analysis shows mixed results regarding the effectiveness of the adaptive ITS for learners with ADHD. Strong support is found for H1, with the adaptive system significantly enhancing trait profiles, reflecting a rise in scores in positive traits like engagement and motivation, while seeing a decrease in negative traits such as inattention and impulsivity. H3 is also supported, demonstrating a significant reduction in perceived cognitive load, reflecting a decrease in cognitive load indicators such as perceived mental load and frustration. However, H2 and H4 are not supported, as no significant differences emerge in user satisfaction or learning performance between the adaptive and non-adaptive ITS groups. This suggests that while the ITS positively influences character traits and cognitive dimensions, these benefits do not translate into measurable learning gains or perceived user satisfaction. This possibly could suggest a disconnect between internal system efficacy and external user perception, highlighting a potential misalignment in how ADHD learners process adaptive interventions.

6.2 Discussion

The strong support for hypothesis 1 leads to a conclusion that confirms key considerations in design translate into measurable outcomes. The significant improvement in trait scores provides strong support for H1. The adaptive ITS demonstrated its greatest impact by markedly reducing impulsivity, frustration, and inattention. This aligns with findings that structured, responsive systems can mitigate the core executive function and emotional dysregulation challenges inherent to ADHD (Barkley, 2015; Shaw et al., 2014). Moreover, the substantial boosts in learner confidence and motivation are consistent with research indicating that personalised, reinforcing feedback effectively targets the motivational deficits associated with ADHD's dopamine pathways (Volkow et al., 2011), creating a more conducive internal state for learning. However, the significance found in the trait profiles could be partly circular. The system's adaptive prompts stimulated on-topic responses, which were then positively scored for traits like improved motivation and reduced impulsivity. This raises doubts about the findings' validity, as the improved scores might reflect the system's structure in guiding behaviour rather than a substantive change in the learner's state. Nonetheless, since a primary design aim was to actively direct user focus, the result demonstrates the effectiveness in this regard. Still, a significant result in user satisfaction would have further strengthened the findings of hypothesis 1, enhancing the robustness of the conclusion, and improved test scores would have indicated that the technique also translates into learning outcomes.

The significant reduction in cognitive load is a standout result. Jabari’s adaptive pacing and specific instructions help tackle ADHD learners’ struggles with cognitive overload, a direct design principle as outlined in section 4.2. The adaptive system's ability to reduce perceived mental demand and frustration indicates that it successfully alleviated the cognitive strain often experienced by individuals with ADHD in traditional learning environments, as detailed by Carlisle (2019) and Evans et al. (2011). Furthermore, the reduction in perceived frustration corroborates the improvements observed in the frustration trait profile in H1. This direct connection between subjective experience found in the cognitive load outcomes and the system's trait analysis lends credibility to both findings. Moreover, the reduction in frustration is significant given that emotional dysregulation is a common challenge for individuals with ADHD (Shaw et al., 2014; Wu et al., 2020). Still, this success is isolated as its lack of translation into learning outcomes hints at a ceiling effect, where reduced load aids comfort but not improved performance. The failed impact on learning and user satisfaction weakens the overall conclusion of hypothesis 3, although promising signs can be concluded. An alternative explanation for the misalignment between the hypotheses could suggest a disconnect between internal system efficacy and external user perception, highlighting a potential discrepancy in how ADHD learners process adaptive interventions. An interesting insight into the results of the cognitive load scores is the variance between different ADHD subtypes. Results show that cognitive load is significantly reduced in the Inattentive and combined subtype, while the Hyperactive/Impulsive subtype shows a slightly higher perceived cognitive load. The split in results can be reasoned through the different impairments in working memory and attentional impulsivity displayed in the different subtypes. The Hyperactive/Impulsive subtype is characterised by deficits in attentional and cognitive impulsivity (Malloy-Diniz et al., 2007), with some theories proposing that learners with ADHD have lower baseline arousal and may use external stimulation to maintain optimal focus (Söderlund et al., 2007). Therefore, an adaptive system that reduces external stimuli might inadvertently increase the cognitive load of this group by forcing them to use internal effort to maintain focus. On the other hand, individuals with inattentive symptoms often struggle with working memory and processing complex information, processes that directly increase cognitive load (Kusumasari et al., 2018; Salomone et al., 2016). Here, an adaptive system that alleviates cognitive load can reduce the struggles found with working memory and information processing. Logically, scores for individuals with a combined subtype are in between these two dominant subtypes.

The lack of significant difference in user satisfaction may depend on uncontrolled factors, such as personal expectations, individual interface preferences, or the relevance of content. A substantial variability in the control group regarding user satisfaction scores indicates inconsistent perceptions of the generic version of the ITS, possibly stemming from a misalignment between pre-experiment expectations and actual system behaviour. Another explanation in line with insights from Morsink et al. (2021) and Shenaq (2021) could be that while the system has provided sufficient support, the nature of its system, external rewards, might not have sufficiently fueled the learners with a sense of intrinsic motivation. The variability in the control group further suggests that a standard ITS, even without adaptive features, can elicit a wide range of user experiences, making it challenging to pinpoint the unique contribution of adaptation to overall satisfaction.

The non-significant result for hypothesis 4 indicates a failure to demonstrate improved learning outcomes, which prevents the study results from being comprehensive (along with user satisfaction). This finding suggests a fundamental disconnect between creating a comfortable learning state and an effective one. Reasoning behind the disconnect could feature the system's success in mitigating cognitive overload, which may have inadvertently removed the desirable difficulty required for robust knowledge consolidation. This aligns with theories suggesting that learners with ADHD require optimal levels of stimulation to maintain focus (Zentall, 2005). When a task's difficulty is reduced too much, it can fail to foster the deep cognitive engagement necessary for learning (Whirley et al., 2003), a principle supported by research showing task difficulty is a critical variable in academic performance (Reed & Martens, 2008). By adapting to reduce frustration and lower complexity at times, Jabari may have prevented learners from engaging in the deeper, more effortful cognitive processing that strengthens memory. Similar to the case of user satisfaction scores, improved trait scores for motivation could be merely a form of extrinsic motivation driven by the system's supportive feedback loop, a strategy known to be effective in the short term (Morris et al., 2023). However, this external scaffolding may not have brought the deeper intrinsic motivation crucial for self-regulated learning (Kusurkar et al., 2011; Morsink et al., 2021). The system successfully supported executive functions by managing the learning environment for the user, but in doing so, it may have reduced the need for learners to actively engage their own planning and self-correction skills (Barkley, 2010). Ultimately, the results show that while managing the cognitive and emotional state of an ADHD learning is achievable and beneficial, it by itself is not sufficient to guarantee enhanced learning outcomes. The results show there is a need for both internal motivation and a “desirable” task difficulty to properly stimulate reducing cognitive load while still promoting cognitive processing (Morsink et al., 2021; Reed & Martens, 2008).

In conclusion, the findings of this study contribute to the literature on adaptive learning for ADHD learners in light of the identified gaps in Section 2.5.2. While previous studies acknowledged the potential of AI interventions for ADHD (Parker et al., 2011; Parker & Boutelle, 2009) and LLMs in education (Kumar et al., 2024), this research uniquely explores their intersection specifically for ADHD learners. The results suggest that LLM-powered adaptive systems can indeed create a more comfortable and internally conducive learning environment for ADHD individuals by dynamically adjusting to their cognitive and emotional states, thus filling a crucial gap in responsive support. However, the lack of significant improvements in user satisfaction and learning performance reveals a partial efficacy, where internal system benefits do not fully translate into user-perceived value or academic gains.

6.3 Limitations

There are several limitations in the study. First, the Swahili test lacked sufficient variety in difficulty, resulting in a narrow range of scores. Furthermore, its reliance on binary scoring may have limited the potential for more variable outcomes. Furthermore, the Gemini 2.0 Flash API was adequate, but more advanced models could have improved the translation of the prompt into natural conversations. The model was limited in its vocal variety and often used repetitive phrasing, which could have weakened its engagement potential. A more advanced model was not feasible due to budget and time constraints. Newer free-to-use models from Google became available towards the end of the design process, but upon testing, they did not align with the prompt design established during an iterative process with Gemini 2.0 Flash. A longer time frame would have provided the opportunity for fine-tuning the design of newer API models, which could have enhanced the ITS. Third, the reliance on purely quantitative data for H2 and H3 (user satisfaction and cognitive load) limited the depth of analysis. Self-reported Likert scales and NASA-TLX scores are subjective and susceptible to uncontrolled factors such as personal expectations or interface preferences, which may have obscured true effects in user satisfaction. Qualitative methods, such as interviews, could have further explored these drivers. Finally, a small limitation of the current system was that the content adaptation logic was sometimes overridden or compromised by the rigid experiment state, which prioritised ensuring all Swahili words were taught sequentially. While content adaptation was present, its potential was not fully realised due to this fixed progression. This meant that even if a learner's traits suggested a need for more varied or exploratory content, the system's core imperative was to move them through the predetermined word list. These limitations underscore the necessity for methodological and design refinements to strengthen the study’s conclusions.

6.4 Future Studies

This thesis confirmed that an LLM-powered ITS can provide the real-time, trait-based responsiveness that existing systems for ADHD learners often lack. It successfully demonstrated that a dynamic, text-only system can positively influence a user's internal state, improving traits and reducing cognitive load, filling a key part of the identified literature gap. However, the findings also revealed a new challenge, which is translating these internal state improvements into learning gains and perceived user satisfaction.

Therefore, future studies must seek to advance from merely managing cognitive states to actively stimulating learning. Research needs to seek designs that test adaptive engines that introduce “desirable difficulty”, using LLMs' reasoning capabilities to not soothe cognitive frustration but to strategically challenge learners to promote deeper cognitive processing. Longitudinal studies are needed to determine if the benefits of boosted trait profiles and reduced cognitive load over time eventually translate into enhanced learning performance. Qualitative methods, such as user interviews, would provide deeper insights into user satisfaction drivers, moving closer to the specific source of learners’ struggles. Employing advanced LLMs, such as newer Gemini models or alternative APIs, with sufficient time for prompt optimisation, could improve conversational adaptability and engagement, potentially boosting the learning experience and its outcomes further.

In conclusion, while the potential of personalised learning for ADHD is significant, this study’s limitations highlight the necessity of future research with more robust methodologies. The primary challenge remains to build upon the proven benefits of cognitive load and user traits, developing systems that convert these internal-state improvements into demonstrable gains in learning outcomes and user satisfaction.

References

- Abraham-Curto, J. (2013). Contributions to improve online learning through adaptive hypermedia techniques. *Research Papers Faculty of Materials Science and Technology Slovak University of Technology, 21*(Special-Issue), 1–6.
- Adler, L. A. (2004). Clinical presentations of adult patients with ADHD. *The Journal of Clinical Psychiatry, 65* (Suppl. 3), 8–11.
- Adler, L. A., Faraone, S. V., Spencer, T. J., Berglund, P., Alperin, S., & Kessler, R. C. (2017). The structure of adult ADHD. *International Journal of Methods in Psychiatric Research, 26*(1), e1555. https://doi.org/10.1002/mpr.1555
- Agarwal, H., Agarwal, D., & Srivastava, P. (2016). Adult attention deficit hyperactivity disorder: A case report. *International Journal of Advances in Medicine, 3*(4), 1080–1081. https://doi.org/10.18 203/2349-3933.ijam20163754
- Ağayeva, K. (2024). Inhibitory control in children with attention deficit and hyperactivity disorder. *Scientific Works, 91*(1), 230–235. https://doi.org/10.69682/azrt.2024.91(1).230-235
- Akavova, A., Temirkhanova, Z., & Lorsanova, Z. M. (2023). Adaptive learning and artificial intelligence in the educational space. *E3S Web of Conferences, 451*, 06011. https://doi.org/10.1051/e3sconf/202345106011
- Al-Emran, M., & Shaalan, K. (2014). A survey of intelligent language tutoring systems. In *2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI)* (pp. 1867–1873). IEEE. https://doi.org/10.1109/icacci.2014.6968503
- Allen, L. K. (2015). Who do you think I am? Modeling individual differences for more adaptive and effective instruction. *Educational Data Mining*, 659–661.
- Alshahrani, E. A., Al-Sarrow, M. I., & Al-Badi, A. H. (2017). Developing an adaptive learning management system based on personalization and real-time feedback. In *2017 6th International Conference on Information and Communication Technology and Accessibility (ICTA)* (pp. 1–6). IEEE.
- Altgassen, M., Scheres, A., & Edel, M.-A. (2019). Prospective memory (partially) mediates the link between ADHD symptoms and procrastination. *ADHD Attention Deficit and Hyperactivity Disorders, 11*(1), 59–71. https://doi.org/10.1007/s12402-018-0273-x
- Arnold, L. E. (2011). How can we improve the diagnosis of attention deficit/hyperactivity disorder? *Neuropsychiatry, 1*(4), 343–351. https://doi.org/10.2217/npy.11.40
- Asherson, P., Manor, I., & Huss, M. (2014). Attention-deficit/hyperactivity disorder in adults: Update on clinical presentation and care. *Neuropsychiatry, 4*(1), 109–128. https://doi.org/10.2217/npy.14.16
- Baggaley, J., Kane, T., & Wade, B. (2002). Online polling services. *The International Review of Research in Open and Distributed Learning, 3*(2). https://doi.org/10.19173/irrodl.v3i2.89
- Bañeres, D., Baró, X., Guerrero-Roldán, A.-E., & Rodríguez, M. E. (2015). Towards a general adaptive e-assessment system. In *2015 International Conference on Intelligent*

Networking and Collaborative Systems (pp. 314–321). IEEE. https://doi.org/10.1109/incos.2015.53

- Barkley, R. A. (1997). Attention-deficit/hyperactivity disorder, self-regulation, and time. *Journal of Developmental & Behavioral Pediatrics, 18*(4), 271–279. https://doi.org/10.1097/00004703-199708000-00009
- Barkley, R. A. (2010). Differential diagnosis of adults with ADHD. *The Journal of Clinical Psychiatry, 71*(7), e17. https://doi.org/10.4088/jcp.9066tx1c
- Barkley, R. A. (2015). *Attention-deficit hyperactivity disorder: A handbook for diagnosis and treatment* (4th ed.). Guilford Press.
- Baskaran, V., Kalaichandar, M., Kirubakaran, K., Kokila, K., Jeevitha, M., & Satheeshkumar, D. (2020). To study prevalence of adult ADHD among patients with intentional self-harm. *International Journal of Pharmacometrics and Integrated Biosciences, 5*(2), 26–31. https://doi.org/10.26452/ijpib.v5i2.1272
- Belmar Mellado, M., Navas Martínez, L., & Holgado Tello, F. P. (2013). Procesos atencionales implicados en el trastorno por déficit de atención con hiperactividad (TDAH). *Revista Convergencia Educativa, (7)*, 1–12.
- Bitsakou, P., Psychogiou, L., Thompson, M., & Sonuga-Barke, E. J. S. (2009). Delay aversion in attention deficit/hyperactivity disorder: An empirical investigation of the broader phenotype. *Neuropsychologia, 47*(2), 446–456. https://doi.org/10.1016/j.neuropsychologia.2008.09.015
- Bradley, W., & Mannell, R. C. (1984). Sensitivity of intrinsic motivation to reward procedure instructions. *Personality and Social Psychology Bulletin, 10*(3), 426–431. https://doi.org/10.1177/0146167284103011
- Bressane, A., Zwirn, D., Essiptchouk, A., Saraiva, A. C. V., Carvalho, F. L. de C., Formiga, J. K. S., Medeiros, L. C. de C., & Negri, R. G. (2024). Understanding the role of study strategies and learning disabilities on student academic performance to enhance educational approaches: A proposal using artificial intelligence. *Computers and Education: Artificial Intelligence, 6*, 100196. https://doi.org/10.1016/j.caeai.2023.100196
- Brim, S. A., & Whitaker, D. P. (2000). Motivation and students with attention deficit hyperactivity disorder. *Preventing School Failure: Alternative Education for Children and Youth, 44*(2), 57–60. https://doi.org/10.1080/10459880009599784
- Brown, T. E. (2006). Executive functions and attention deficit hyperactivity disorder: Implications of two conflicting views. *International Journal of Disability, Development and Education, 53*(1), 35–46. https://doi.org/10.1080/10349120500510024
- Buckley, P., & Doyle, E. (2014). Gamification and student motivation. *Interactive Learning Environments, 24*(6), 1162–1175. https://doi.org/10.1080/10494820.2014.964263
- Burns, E., & Martin, A. J. (2014). ADHD and adaptability: The roles of cognitive, behavioural, and emotional regulation. *Australian Journal of Guidance and Counselling, 24*(2), 227–242. https://doi.org/10.1017/jgc.2014.17
- Carlisle, N. (2019). Flexibility in attentional control: Multiple sources and suppression. *PubMed, 92*(1), 103–113.

- Carlson, R., Chandler, P., & Sweller, J. (2003). Learning and understanding science instructional material. *Journal of Educational Psychology, 95*(3), 629–640. https://doi.org/10.1037/0022-0663.95.3.629
- Chadha, A. (2022). Pedagogical interrelationships. *Journal of the Scholarship of Teaching and Learning, 22*(2). https://doi.org/10.14434/josotl.v22i2.31626
- Cheng, H., Chen, S., Perdriau, C., & Huang, Y. (2024). LLM-powered AI tutors with personas for d/Deaf and hard-of-hearing online learners.
- Cohen, M. W., & Beattie, J. R. (1984). What works with LD adolescents? *Academic Therapy, 19*(4), 397–402. https://doi.org/10.1177/105345128401900402
- Conati, C., & Kardan, S. (2013). Student modeling: Supporting personalized instruction, from problem solving to exploratory open ended activities. *AI Magazine, 34*(3), 13–26. https://doi.org/10.1609/aimag.v34i3.2483
- Cornelius, S., Gordon, C., & Ackland, A. (2009). Towards flexible learning for adult learners in professional contexts: An activity-focused course design. *Interactive Learning Environments, 19*(4), 381–393. https://doi.org/10.1080/10494820903298258
- Cubbin, S., Leaver, L., & Parry, A. (2020). Attention deficit hyperactivity disorder in adults: Common in primary care, misdiagnosed, and impairing, but highly responsive to treatment. *British Journal of General Practice, 70*(698), 465–466. https://doi.org/10.3399/bjgp20x712553
- de Almeida Souza, M. R., Constantino, K., Veado, L. F., & Figueiredo, E. (2017). *Gamification in software engineering education: An empirical study*.
- Decaires-Wagner, A. (2017). The social and emotional development of the ADHD child. *Mental Health Matters, 4*(1), 20–22.
- Del Soldato, T., & du Boulay, B. (1995). Implementation of motivational tactics in tutoring systems. *Journal of Artificial Intelligence in Education, 6*(4), 337–378.
- Dobre, I. (2014). Student’s knowledge assessment through an intelligent tutoring system using natural language processing based on an automatic system for generating questions. *eLearning and Software for Education, 2*, 150–155. https://doi.org/10.12753/2066-026x-14-076
- Doyle, A. E. (2006). Executive functions in attention-deficit/hyperactivity disorder. *The Journal of Clinical Psychiatry, 67*(Suppl. 8), 21–26.
- Edathil, S., Chin, C., Zank, S., Ranmuthugala, D., & Salter, S. (2014). Development of an application with process feedback to enhance student-centred learning. *ASCILITE Publications*, 394–398. https://doi.org/10.14742/apubs.2014.1177
- Edmundson, P. J. (2008). Helping adults learn. *Journal of Teaching in the Addictions, 6*(1), 59–70. https://doi.org/10.1080/15332700802126377
- Elkins, S., Belfer, R., Kochmar, E., Serban, I., & Cheung, J. C. K. (2022). Question personalization in an intelligent tutoring system. In *Proceedings of the 17th Workshop on Innovative Use of NLP for Building Educational Applications* (pp. 98–106). Association for Computational Linguistics.
- Erradi, M., El Hore, E. M., & Benchikha, O. (2023). An intelligent learning management system using machine learning for personalized learning paths recommendation. *International Journal of Information and Education Technology, 13*(4), 604–611.

- Evans, K. K., Horowitz, T. S., Howe, P., Pedersini, R., Reijnen, E., Pinto, Y., Kuzmova, Y., & Wolfe, J. M. (2011). Visual attention. *WIREs Cognitive Science, 2*(5), 503–514. https://doi.org/10.1002/wcs.127
- Gupta, T. R. (2024). Adaptive learning systems: Harnessing AI to personalize educational outcomes. *International Journal for Research in Applied Science and Engineering Technology, 12*(11), 458–464. https://doi.org/10.22214/ijraset.2024.65088
- Fabio, R. A., & Caprì, T. (2017). The executive functions in a sample of Italian adults with ADHD: Attention, response inhibition and planning/organization. *Mediterranean Journal of Clinical Psychology, 5*(3). https://doi.org/10.6092/2282-1619/2017.5.1636
- Farrow, E., Moore, J., & Gašević, D. (2019). Analysing discussion forum data. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge* (pp. 170–174). ACM. https://doi.org/10.1145/3303772.3303779
- Fen, S., & Ma, Y. (2020). How to enhance focused attention of organization members on their learning process. *American Journal of Industrial and Business Management, 10*(6), 1155–1161. https://doi.org/10.4236/ajibm.2020.106078
- Feng-cun, L. (2008). The connotation and characteristics of self-regulated learning of the adult students in the modern distance education environment. *Journal of Jiangsu Teachers University of Technology*.
- Fini, E. (2010). Incorporating a real-world case study into a senior construction engineering course. *Journal of STEM Education: Innovations and Research, 11*(5–6), 47–54.
- Forster, S., Robertson, D. J., Jennings, A., Asherson, P., & Lavie, N. (2013). Plugging the attention deficit: Perceptual load counters increased distraction in ADHD. *Neuropsychology, 28*(1), 91–97. https://doi.org/10.1037/neu0000020
- Fosco, W. D., Hawk, L. W., Jr., Rosch, K. S., & Bubnik, M. G. (2015). Evaluating cognitive and motivational accounts of greater reinforcement effects among children with attention-deficit/hyperactivity disorder. *Behavioral and Brain Functions, 11*(1). https://doi.org/10.1186/s12993-015-0065-9
- Friedman-Hill, S. R., Wagman, M. R., Gex, S. E., Pine, D. S., Leibenluft, E., & Ungerleider, L. G. (2010). What does distractibility in ADHD reveal about mechanisms for top-down attentional control? *Cognition, 115*(1), 93–103. https://doi.org/10.1016/j.cognition.2009.11.013
- Fuermaier, A. B. M., Tucha, L., Koerts, J., Aschenbrenner, S., Westermann, C., Weisbrod, M., Lange, K. W., & Tucha, O. (2013). Complex prospective memory in adults with attention deficit hyperactivity disorder. *PLoS ONE, 8*(3), e58338. https://doi.org/10.1371/journal.pone.0058338
- Funk, P., & Conlan, O. (2002). Case-based reasoning and knowledge management to improve adaptability of intelligent tutoring systems. In *Proceedings of the International Conference on Case-Based Reasoning* (pp. 351–365). Springer.
- Furukawa, E., Alsop, B., Alves, H., Vorderstrasse, V., Carrasco, K., Chuang, C.-C., & Tripp, G. (2022). Disrupted waiting behavior in ADHD: Exploring the impact of reward availability and predictive cues. *Child Neuropsychology, 29*(1), 76–95. https://doi.org/10.1080/09297049.2022.2068518

- Gabay, Y., Shahbari-Khateb, E., & Mendelsohn, A. (2018). Feedback timing modulates probabilistic learning in adults with ADHD. *Scientific Reports, 8*(1). https://doi.org/10.1038/s41598-018-33551-3
- González-Sánchez, M., Lavigne-Cerván, R., Romero, J. F., & Elósegui, E. (2019). Emotion regulation in participants diagnosed with attention deficit hyperactivity disorder, before and after an emotion regulation intervention. *Frontiers in Psychology, 10*, 1092. https://doi.org/10.3389/fpsyg.2019.01092
- Gorbunovs, A., Timsans, Z., Zuga, B., & Zagorskis, V. (2018). Conceptual design of the new generation adaptive learning management system. *International Journal of Engineering & Technology, 7*(2.28), 129. https://doi.org/10.14419/ijet.v7i2.28.12894
- Google Cloud. (2025). Server-side encryption. https://cloud.google.com/firestore/native/docs/server-side-encryption.
- Gündogan, M. B. (2000). Awareness of ergonomics in user interface design of instructional websites. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 44*(4), 481–484. https://doi.org/10.1177/154193120004400421
- Haddad, R., & Kalaani, Y. (2014). Google Forms: A real-time formative feedback process for adaptive learning. In *2014 ASEE Annual Conference & Exposition Proceedings*. ASEE. https://doi.org/10.18260/1-2--20540
- Hafidi, M., & Bensebaa, T. (2014). Developing adaptive and intelligent tutoring systems (AITS). *International Journal of Information and Communication Technology Education, 10*(4), 70–85. https://doi.org/10.4018/ijicte.2014100106
- Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. *Advances in Psychology, 52*, 139–183.
- Hart Barnett, J. E. (2017). Helping students with ADHD in the age of digital distraction. *Research Advocacy and Practice for Complex and Chronic Conditions, 36*(2), 1–7. https://doi.org/10.14434/pders.v36i2.23913
- Hernández, Y., Morales, R., & Mayora, O. (2004). Modeling affective responses in intelligent tutoring systems. In *Proceedings of the IEEE International Conference on Advanced Learning Technologies* (pp. 926–928). IEEE. https://doi.org/10.1109/icalt.2004.1357644
- Higgins, T. P. (2007). Teaching strategies for students with attention deficit hyperactivity disorder. *Regis University Student Publications*.
- Johnson, J., & Reid, R. (2011). Overcoming executive function deficits with students with ADHD. *Theory Into Practice, 50*(1), 61–67. https://doi.org/10.1080/00405841.2010.534942
- Kahn, M. J., Tan, K. C., & Beaton, R. J. (1990). Reduction of cognitive workload through information chunking. *Proceedings of the Human Factors Society Annual Meeting, 34*(19), 1509–1513. https://doi.org/10.1177/154193129003401919
- Katiyar, N., Awasthi, V. K., Pratap, R., Mishra, K., Shukla, N., Singh, R., & Tiwari, M. (2024). AI-driven personalized learning systems: Enhancing educational effectiveness. *Educational Administration: Theory and Practice, 30*(5), 4961–4968. https://doi.org/10.53555/kuey.v30i5.4961
- Kaur, G., Walvekar, S., Thawkar, B., & Chintamaneni, M. (2022). Recent advances of artificial intelligence tools in attention-deficit hyperactivity disorder (ADHD). *Current*

Psychopharmacology, 11(1), 18–29. https://doi.org/10.2174/2211556011666220607112528

- Kirby, A. (2009). Understanding attention deficit hyperactivity disorder. *Independent Nurse, 2009*(5). https://doi.org/10.12968/indn.2009.18.5.76687
- Knouse, L. E., Anastopoulos, A. D., & Dunlosky, J. (2011). Isolating metamemory deficits in the self-regulated learning of adults with ADHD. *Journal of Attention Disorders, 16*(8), 650–660. https://doi.org/10.1177/1087054711417231
- Kosch, T., Hassib, M., Buschek, D., & Schmidt, A. (2018). Look into my eyes. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems* (pp. 1–6). ACM. https://doi.org/10.1145/3170427.3188643
- Král, J., & Čápek, R. (2016). Using build and runtime information for student adaptive support. In *2016 International Conference on Computational Science and Computational Intelligence (CSCI)* (pp. 139–144). IEEE. https://doi.org/10.1109/csci.2016.0264
- Kumar, H., Musabirov, I., Reza, M., Shi, J., Wang, X., Williams, J. J., Kuzminykh, A., & Liut, M. (2024). Guiding students in using LLMs in supported learning environments: Effects on interaction dynamics, learner performance, confidence, and trust. *Proceedings of the ACM on Human-Computer Interaction, 8*(CSCW2), 1–30. https://doi.org/10.1145/3687038
- Kusumasari, D., Junaedi, D., & Kaburuan, E. R. (2018). Designing an interactive learning application for ADHD children. *MATEC Web of Conferences, 197*, 16008. https://doi.org/10.1051/matecconf/201819716008
- Kusurkar, R. A., Croiset, G., & Ten Cate, O. Th. J. (2011). Twelve tips to stimulate intrinsic motivation in students through autonomy-supportive classroom teaching derived from self-determination theory. *Medical Teacher, 33*(12), 978–982. https://doi.org/10.3109/0142159x.2011.599896
- Lee, D. L., & Asplen, J. (2004). Using color to increase the math persistence of children with co-occurring learning disabilities and attentional deficits. *Learning Disabilities: A Multidisciplinary Journal, 13*(2), 55–60.
- Likert, R. (1932). A technique for the measurement of attitudes. *Archives of Psychology, 140*, 1–55.
- Liu, Z., Yin, S. X., Lin, G., & Chen, N. F. (2024). *Personality-aware student simulation for conversational intelligent tutoring systems*. arXiv.
- Lorch, E. P., Milich, R., Astrin, C. C., & Berthiaume, K. S. (2006). Cognitive engagement and story comprehension in typically developing children and children with ADHD from preschool through elementary school. *Developmental Psychology, 42*(6), 1206–1219. https://doi.org/10.1037/0012-1649.42.6.1206
- Luo, X. (2024). Learning analytics based on big data: Student behavior prediction and personalized educational strategy formulation. *Applied and Computational Engineering, 100*(1), 7–13. https://doi.org/10.54254/2755-2721/100/20251732
- Luarn, P., Chen, C.-C., & Chiu, Y.-P. (2023). Enhancing intrinsic learning motivation through gamification: A self-determination theory perspective. *The International Journal of Information and Learning Technology, 40*(5), 413–424. https://doi.org/10.1108/ijilt-07-2022-0145

- Lydia, E. G., Vidhyavathi, P., & Malathi, P. (2023). A study on AI in education: Opportunities and challenges for personalized learning. *Industrial Engineering Journal, 52*(5), 750–759. https://doi.org/10.36893/iej.2023.v52i05.750-759
- Magon, R., & Müller, U. (2012). ADHD with comorbid substance use disorder: Review of treatment. *Advances in Psychiatric Treatment, 18*(6), 436–446. https://doi.org/10.1192/apt.bp.111.009340
- Malloy-Diniz, L., Fuentes, D., Leite, W. B., Correa, H., & Bechara, A. (2007). Impulsive behavior in adults with attention deficit/hyperactivity disorder: Characterization of attentional, motor and cognitive impulsiveness. *Journal of the International Neuropsychological Society, 13*(4), 693–698. https://doi.org/10.1017/s1355617707070889
- Mancera, L., Baldiris, S., Fabregat, R., Vinas, F., & Caparros, B. (2011). Adapting suitable spaces in learning management systems to support distance learning in adults with ADHD. In *2011 IEEE 11th International Conference on Advanced Learning Technologies* (pp. 103–107). IEEE. https://doi.org/10.1109/icalt.2011.37
- Manz, C. C., & Manz, K. P. (1991). Strategies for facilitating self-directed learning: A process for enhancing human resource development. *Human Resource Development Quarterly, 2*(1), 3–12. https://doi.org/10.1002/hrdq.3920020103
- Masi, L. (2015). ADHD and comorbid disorders in childhood psychiatric problems, medical problems, learning disorders and developmental coordination disorder. *Clinical Psychiatry, 1*(1). https://doi.org/10.21767/2471-9854.100005
- Mathew, A. N., V., R., & Paulose, J. (2021). NLP-based personal learning assistant for school education. *International Journal of Electrical and Computer Engineering (IJECE), 11*(5), 4522–4530. https://doi.org/10.11591/ijece.v11i5.pp4522-4530
- McCrickard, D. S., Catrambone, R., Chewar, C. M., & Stasko, J. T. (2003). Establishing tradeoffs that leverage attention for utility: Empirically evaluating information display in notification systems. *International Journal of Human-Computer Studies, 58*(5), 547–582. https://doi.org/10.1016/s1071-5819(03)00022-3
- McNamara, A., Kabeerdoss, C., & Egan, C. (2015). Mobile user interfaces based on user attention. In *Proceedings of the 2015 Workshop on Future Mobile User Interfaces* (pp. 1–6). ACM. https://doi.org/10.1145/2754633.2754634
- Mohammed, M., Fatemah, A., & Hassan, L. (2024). Effects of gamification on motivations of elementary school students: An action research field experiment. *Simulation & Gaming, 55*(4), 600–636. https://doi.org/10.1177/10468781241237389
- Molitor, S. J., Oddo, L. E., Eadeh, H.-M., & Langberg, J. M. (2018). Executive function deficits in adolescents with ADHD: Untangling possible sources of heterogeneity. *Journal of Emotional and Behavioral Disorders, 27*(3), 165–177. https://doi.org/10.1177/1063426618763125
- Montano, C. B., & Weisler, R. H. (2011). Distinguishing symptoms of ADHD from other psychiatric disorders in the adult primary care setting. *Postgraduate Medicine, 123*(3), 88–98. https://doi.org/10.3810/pgm.2011.05.2287
- Morales-Chan, M., Amado-Salvatierra, H. R., Medina, J. A., Barchino, R., Hernández-Rizzardini, R., & Teixeira, S. M. (2024). Personalized feedback in massive

open online courses: Harnessing the power of LangChain and OpenAI API. *Electronics, 13*(10), 1960. https://doi.org/10.3390/electronics13101960

- Morris, S. S. J., Raiker, J. S., Mattfeld, A. T., & Fosco, W. D. (2023). The impact of ADHD symptom severity on reinforcement and punishment learning among adults. *Cognitive Neuropsychiatry, 28*(2), 147–161. https://doi.org/10.1080/13546805.2023.2178398
- Morsink, S., Van der Oord, S., Antrop, I., Danckaerts, M., & Scheres, A. (2021). Studying motivation in ADHD: The role of internal motives and the relevance of self-determination theory. *Journal of Attention Disorders, 25*(8), 1139–1150. https://doi.org/10.1177/10870547211050948
- Mostert, J. C., Onnink, A. M. H., Klein, M., Dammers, J., Harneit, A., Schulten, T., van Hulzen, K. J. E., Kan, C. C., Slaats-Willemse, D., Buitelaar, J. K., Franke, B., & Hoogman, M. (2015). Cognitive heterogeneity in adult attention deficit/hyperactivity disorder: A systematic analysis of neuropsychological measurements. *European Neuropsychopharmacology, 25*(11), 2062–2074. https://doi.org/10.1016/j.euroneuro.2015.08.010
- Namkoong, S., Ahn, D.-H., & Lee, Y. (2007). The learning motivation improvement program in children with attention-deficit hyperactivity disorder (ADHD). *Journal of Korean Academy of Child and Adolescent Psychiatry, 18*(1), 58–65.
- Niermann, H. C. M., & Scheres, A. (2014). The relation between procrastination and symptoms of attention-deficit hyperactivity disorder (ADHD) in undergraduate students. *International Journal of Methods in Psychiatric Research, 23*(4), 411–421. https://doi.org/10.1002/mpr.1440
- Noguera, J., Ayeni, F., Okuboyejo, S., & Adusumilli, S. (2017). Towards a web-based adaptive and intelligent tutoring system. *International Journal of Computing, 1*(1), 45–52.
- Ogrodnik, M., Karsan, S., Malamis, B., Kwan, M., Fenesi, B., & Heisz, J. J. (2023). Exploring barriers and facilitators to physical activity in adults with ADHD: A qualitative investigation. *Journal of Developmental and Physical Disabilities, 36*(2), 307–327. https://doi.org/10.1007/s10882-023-09908-6
- Oguchi, M., Takahashi, T., Nitta, Y., & Kumano, H. (2023). Moderating effect of attention deficit hyperactivity disorder tendency on the relationship between delay discounting and procrastination in young adulthood. *Heliyon, 9*(4), e14834. https://doi.org/10.1016/j.heliyon.2023.e14834
- Ohene-Djan, J., & Gorle, M. (2003). An adaptive function for hypermedia-based advanced learning technology. In *Proceedings 3rd IEEE International Conference on Advanced Technologies* (pp. 296–300). IEEE. https://doi.org/10.1109/icalt.2003.1215187
- Okpo, J., Masthoff, J., Dennis, M., & Beacham, N. (2017). Conceptualizing a framework for adaptive exercise selection with personality as a major learner characteristic. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization* (pp. 293–298). ACM. https://doi.org/10.1145/3099023.3099078
- Olagunju, A. E., & Ghoddusi, F. (1994). Attention deficit hyperactivity disorder in adults. *American Journal of Psychiatry, 151*(5), 633–638. https://doi.org/10.1176/ajp.151.5.633
- Olivier, T., & Steenkamp, D. (2003). Attention deficit hyperactivity disorder (ADHD) and intrinsic motivation. *Acta Academica, 35*(3), 116–137.

- Pardosi, B. A., Purba, B., & Hariyanto, A. (2024). Enhancing learning experiences: The integration of artificial intelligence into learning management systems. In *2024 1st International Conference on Computer Science, Engineering, and Information Technology (ICCSEIT)* (pp. 1–6). IEEE.
- Parker, D. R., & Boutelle, K. (2009). Executive function coaching for college students with learning disabilities and ADHD: A new approach for fostering self-determination. *Learning Disabilities Research & Practice, 24*(4), 204–215. https://doi.org/10.1111/j.1540-5826.2009.00294.x
- Parker, D. R., Hoffman, S. F., Sawilowsky, S. S., & Rolands, L. (2011). An examination of the effects of ADHD coaching on university students' executive functioning. *Journal of Postsecondary Education and Disability, 24*(2), 115–132.
- Penningroth, S. L., & Rosenberg, S. (1995). Effects of a high information-processing load on the writing process and the story written. *Applied Psycholinguistics, 16*(2), 189–210. https://doi.org/10.1017/s0142716400007086
- Pievsky, M. A., & McGrath, R. E. (2018). The neurocognitive profile of attention-deficit/hyperactivity disorder: A review of meta-analyses. *Archives of Clinical Neuropsychology, 33*(2), 143–157. https://doi.org/10.1093/arclin/acx055
- Piñeiro-Dieguez, B., Balanzá-Martínez, V., García-García, P., & Soler-López, B. (2016). Psychiatric comorbidity at the time of diagnosis in adults with ADHD. *Journal of Attention Disorders, 20*(12), 1066–1075. https://doi.org/10.1177/1087054713518240
- Pinho, S. A., & Coutinho, F. (2024). Navigating the professional journey for adults with attention deficit/hyperactivity disorder: Challenges and strategies. *European Psychiatry, 67*(S1), S224. https://doi.org/10.1192/j.eurpsy.2024.478
- Plaza Casado, P., Escamilla Solano, S., & Orden-Cruz, C. (2020). Student motivation in a real investment decision-making case study. *Journal of Management and Business Education, 3*(3), 250–265. https://doi.org/10.35564/jmbe.2020.0016
- Pombo, N., & Santos, H. (2023). Lessons learned from the development of a computerized badge-based reward tool for student engagement in learning activities. In *2023 IEEE World Engineering Education Conference (EDUNINE)* (pp. 1–5). IEEE. https://doi.org/10.1109/edunine57531.2023.10102849
- Prevatt, F., Smith, S. M., Diers, S., Marshall, D., Coleman, J., Valler, E., & Miller, N. (2017). ADHD coaching with college students: Exploring the processes involved in motivation and goal completion. *Journal of College Student Psychotherapy, 31*(2), 93–111. https://doi.org/10.1080/87568225.2016.1240597
- Puertas, E., Mariscal-Vivas, G., & Martínez-Requejo, S. (2023). Development of chatbots connected to learning management systems for the support and formative assessment of students. In *Proceedings of the 2023 7th International Conference on Education and E-Learning* (pp. 14–18). ACM. https://doi.org/10.1145/3637989.3637998
- Randall, K. D., Brocki, K. C., & Kerns, K. A. (2009). Cognitive control in children with ADHD-C: How efficient are they? *Child Neuropsychology, 15*(2), 163–178. https://doi.org/10.1080/09297040802464148
- Ravichandran, S., & Jacklyn, H. Q. (2009). Behavior modification strategy for motivating children with attention deficiency disorder. In *Proceedings of the 3rd International*

Convention on Rehabilitation Engineering & Assistive Technology (Article 49). ACM. https://doi.org/10.1145/1592700.1592740

- Reed, D. D., & Martens, B. K. (2008). Sensitivity and bias under conditions of equal and unequal academic task difficulty. *Journal of Applied Behavior Analysis, 41*(1), 39–52. https://doi.org/10.1901/jaba.2008.41-39
- Richman, E. L., Rademacher, K., & Maitland, T. L. (2014). Coaching and college success. *Journal of Postsecondary Education and Disability, 27*(1), 33–50.
- Rizvi, M. (2023). Investigating AI-powered tutoring systems that adapt to individual student needs, providing personalized guidance and assessments. *The Eurasia Proceedings of Educational and Social Sciences, 31*, 67–73. https://doi.org/10.55549/epess.1381518
- Rocha, P. A., Oliveira, V. M. de, & Martins, A. L. de A. (2024). Aggression and criminality in adults with ADHD. *LUMEN ET VIRTUS, 15*(40), 1–12. https://doi.org/10.56238/levv15n40-062
- Rodrigues, L., Toda, A. M., Oliveira, W., Palomino, P. T., Avila-Santos, A. P., & Isotani, S. (2021). Gamification works, but how and to whom? In *Proceedings of the 52nd ACM Technical Symposium on Computer Science Education* (pp. 968–974). ACM. https://doi.org/10.1145/3408877.3432419
- Rose, J. A., O'Meara, J. M., Gerhardt, T. C., & Williams, M. (2016). Gamification: Using elements of video games to improve engagement in an undergraduate physics class. *Physics Education, 51*(5), 055007. https://doi.org/10.1088/0031-9120/51/5/055007
- RUG, Faculty of Economics and Business. (2025). Data protection and student research: WE privacy & security.
- Sady, M. D., Barrett-Clarke, A. P., Gioia, G. A., Harrison, A. G., Isquith, P. K., & Roth, R. M. (2024). Profile analysis of executive functioning in adults with developmental disorders on the Behavior Rating Inventory of Executive Function, Second Edition—Adult Version (BRIEF2A). *Archives of Clinical Neuropsychology, 39*(7), 1165. https://doi.org/10.1093/arclin/acae067.231
- Sailer, M., Hense, J. U., Mayr, S. K., & Mandl, H. (2017). How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction. *Computers in Human Behavior, 69*, 371–380. https://doi.org/10.1016/j.chb.2016.12.033
- Salameh, W. A. K. (2024). The dual role of AI in personalized learning: Enhancements and hindrances for diverse learners. *International Journal of Science and Research Archive, 13*(2), 62–67. https://doi.org/10.30574/ijsra.2024.13.2.2057
- Salomone, S., Fleming, G. R., Bramham, J., O'Connell, R. G., & Robertson, I. H. (2016). Neuropsychological deficits in adult ADHD: Evidence for differential attentional impairments, deficient executive functions, and high self-reported functional impairments. *Journal of Attention Disorders, 24*(10), 1413–1424. https://doi.org/10.1177/1087054715623045
- Sani, S. M., Bichi, A. B., & Ayuba, S. (2016). Artificial intelligence approaches in student modeling: Half decade review (2010–2015). *International Journal of Computer Science and Information Security, 14*(7), 112–120.

- Sangheethaa, S., & Korath, A. (2024). Impact of AI in education through a teacher's perspective. *Educational Administration: Theory and Practice, 30*(4), 1349–1356. https://doi.org/10.53555/kuey.v30i4.1349
- Santos, S. M. A. V., Da Silva, C. G., De Carvalho, I. E., De Castilho, L. P., Meroto, M. B. das N., Tavares, P. R., Pires, R. dos R., & Moniz, S. S. de O. R. (2024). The art of personalization of education: Artificial intelligence on the stages of special education. *Contribuciones a las Ciencias Sociales, 17*(2), e4971. https://doi.org/10.55905/revconv.17n.2-008
- Scime, M., & Norvilitis, J. M. (2006). Task performance and response to frustration in children with attention deficit hyperactivity disorder. *Psychology in the Schools, 43*(3), 377–386. https://doi.org/10.1002/pits.20151
- Schöbel, S. M., Janson, A., & Leimeister, J. M. (2022). Gamifying online training in management education to support emotional engagement and problem-solving skills. *Journal of Management Education, 47*(2), 166–203. https://doi.org/10.1177/10525629221123287
- Shao-ga, X. (2015). On connotation, elements and functions of adult autonomous learning ability.
- Shaw, P., Stringaris, A., Nigg, J., & Leibenluft, E. (2014). Emotion dysregulation in attention deficit hyperactivity disorder. *American Journal of Psychiatry, 171*(3), 276–293. https://doi.org/10.1176/appi.ajp.2013.13070966
- Shenaq, R. (2021). The effects of extrinsic rewards on intrinsic motivation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3787811
- Sinclair, E., Guthrie, D., & Forness, S. R. (1984). Establishing a connection between severity of learning disabilities and classroom attention problems. *The Journal of Educational Research, 78*(1), 18–21. https://doi.org/10.1080/00220671.1984.10885565
- Sinha, P., Sagar, R., & Mehta, M. (2008). Executive function in attention deficit/hyperactivity disorder. *Journal of Indian Association for Child and Adolescent Mental Health, 4*(2), 44–49. https://doi.org/10.1177/0973134220080204
- Skedsmo, G., & Huber, S. G. (2022). Assessment as a policy instrument and/or tool for professional development. *Educational Assessment, Evaluation and Accountability, 34*(4), 423–425. https://doi.org/10.1007/s11092-022-09402-1
- Slamka, M., Medina, S., & Kreider, C. (2021). Time challenges and well-being for college students with learning disabilities and attention deficit hyperactivity disorder: A qualitative study. *The American Journal of Occupational Therapy, 75*(Supplement_2), 7512505128p1. https://doi.org/10.5014/ajot.2021.75s2-po128
- Söderlund, G., Sikström, S., & Smart, A. (2007). Listen to the noise: Noise is beneficial for cognitive performance in ADHD. *Journal of Child Psychology and Psychiatry, 48*(8), 840–847. https://doi.org/10.1111/j.1469-7610.2007.01749.x
- Soelistianto, F. A., Andrasmoro, D., Yusriati, Y., Mardiati, M., & Fawait, A. B. (2024). The impact of adaptive learning technology on improving students' concept understanding. *Journal of Computer Science Advancements, 2*(3), 158–175. https://doi.org/10.70177/jsca.v2i3.1176
- Song, D., Xu, H., Yu, T., & Tavares, A. (2017). An enjoyable learning experience in personalising learning based on knowledge management: A case study. *EURASIA*

Journal of Mathematics, Science and Technology Education, 13(7), 3001–3018. https://doi.org/10.12973/eurasia.2017.00702a

- Subhankar, S., & Aniket, D. (2024). A deep learning framework for recognizing developmental disorders. *International Journal for Research in Applied Science and Engineering Technology, 11*(3), 1794–1797. https://doi.org/10.22214/ijraset.2023.49796
- Sugiarso, B. A., Nurjamin, A., Judijanto, L., Firdausiyah, L., & Hidayat, A. A. (2024). The effect of artificial intelligence in improving student learning achievement in high school. *World Psychology, 3*(1), 1–14. https://doi.org/10.55849/wp.v3i1.569
- Suhailan, S., Shibghatullah, A. S., & Burhanuddin, M. A. (2014). A perspective of automated programming error feedback approaches in problem solving exercises. *International Journal of Computer Science and Information Security, 12*(6), 45–50.
- Suppawittaya, P. Y. (2021). The effectiveness of chunking methods for enhancing short-term memory of textual information. *Psychology and Education Journal, 57*(9), 6313–6327. https://doi.org/10.17762/pae.v57i9.2963
- Swathilakshmi, P., et al. (2021). Student Suite+: A closed domain question answering system for educational domain. *Turkish Journal of Computer and Mathematics Education (TURCOMAT), 12*(10), 3168–3172. https://doi.org/10.17762/turcomat.v12i10.4974
- Tachmazidis, I., Chen, T., Adamou, M., & Antoniou, G. (2020). A hybrid AI approach for supporting clinical diagnosis of attention deficit hyperactivity disorder (ADHD) in adults. *Health Information Science and Systems, 9*(1). https://doi.org/10.1007/s13755-020-00123-7
- Thawalampola O., Jayasuriya D., Kariyawasam S, Makawita M., Wijendra D. and Joseph J., "Adaptive Learning Tool to Enhance Educational Outcomes for Students with Inattentive Attention Deficit Hyperactivity Disorder (ADHD)," *2024 6th International Conference on Advancements in Computing (ICAC)*, Colombo, Sri Lanka, 2024, pp. 462-467, doi: 10.1109/ICAC64487.2024.10850982.
- Thompson, J. E. (1996). Student modeling in an intelligent tutoring system.
- Tjarve-Golubeva, V., & Rozenfelde, M. (2016). Attention correction possibility in primary school during educating process in special schools for pupils with intellectual disturbances. *Education Reform in Comprehensive School: Education Content Research and Implementation Problems*, 63–73. https://doi.org/10.17770/ercs2015.1144
- Tzuriel, D., Trabelsi, G., & Shomron, V. (2017). The effects of intervention for self-regulation and planning on executive functions, metacognitive awareness and math performance among college students with ADHD. In *EDULEARN Proceedings* (pp. 97–105). IATED. https://doi.org/10.21125/edulearn.2017.0197
- Vaca, J. M., Agudo, J. E., & Rico, M. (2012). Adaptive competence-based system in an e-learning platform: Adapting support tasks to students. In *2012 IEEE 12th International Conference on Advanced Learning Technologies* (pp. 564–568). IEEE. https://doi.org/10.1109/icalt.2012.173
- van der Vorst, T., & Jelicic, N. (2019). Artificial intelligence in education: Can AI bring the full potential of personalized learning to education? *Econstor*.
- Varrasi, S., Boccaccio, F. M., Guerrera, C. S., Platania, G. A., Pirrone, C., & Castellano, S. (2022). Schooling and occupational outcomes in adults with ADHD: Predictors of

success and support strategies for effective learning. *Education Sciences, 13*(1), 37. https://doi.org/10.3390/educsci13010037

- Vemury, C. M., & Devlin, M. (2009). Personalised approach to learner autonomy. In *20th Annual Conference for the Australasian Association for Engineering Education, 6-9 December 2009: Engineering the Curriculum* (pp. 150–155). Engineers Australia.
- Ventouri, E. (2020). ADHD and learning motivations. *OALib, 7*(8), 1–28. https://doi.org/10.4236/oalib.1106594
- Virone, M. L. (2021). The use of mindfulness to improve emotional regulation and impulse control among adolescents with ADHD. *Journal of Occupational Therapy, Schools, & Early Intervention, 14*(4), 403–415. https://doi.org/10.1080/19411243.2021.2009081
- Volkow, N. D., Wang, G.-J., Newcorn, J. H., Kollins, S. H., Wigal, T. L., Telang, F., Fowler, J. S., Goldstein, R. Z., Klein, N., & Swanson, J. M. (2011). Motivation deficit in ADHD is associated with dysfunction of the dopamine reward pathway. *Molecular Psychiatry, 16*(9), 1147–1154. https://doi.org/10.1038/mp.2010.97
- Liu, Q., Wang, W., & Willard, J. (2025). Effects of prompt length on domain-specific tasks for large language models. *arXiv*. https://arxiv.org/abs/2502.14255
- Weinstein, C. S. (1994). Cognitive remediation strategies: An adjunct to the psychotherapy of adults with attention-deficit hyperactivity disorder. *PubMed*.
- Welkie, J., Babinski, D. E., & Neely, K. A. (2020). Sex and emotion regulation difficulties contribute to depression in young adults with attention-deficit/hyperactivity disorder. *Psychological Reports, 124*(2), 596–610. https://doi.org/10.1177/0033294120918803
- White, H., & Shah, P. (2016). Scope of semantic activation and innovative thinking in college students with ADHD. *Creativity Research Journal, 28*(3), 275–282. https://doi.org/10.1080/10400419.2016.1195655
- Whirley, K. S., Lorch, E. P., Lemberger, C., & Milich, R. (2003). Online cognitive engagement of boys with ADHD. *Journal of Attention Disorders, 7*(2), 71–81. https://doi.org/10.1177/108705470300700201
- Willoughby, D., & Evans, M. A. (2019). Self-regulation and academic achievement among college students with ADHD: A scoping review. *Journal of Postsecondary Education and Disability, 32*(2), 115–132.
- Wu, Y., Hu, Z., & Liu, H. (2020). Emotion dysregulation and mechanisms in attention deficit hyperactivity disorder. *Zhonghua Xingwei Yixue yu Naokexue Zazhi, 29*(1), 84–88. https://doi.org/10.3760/cma.j.cn371468-20190527-00343
- Xu, Y., Zhou, X., & Wang, L. (2004). Effects of distractors on sustained attention in children with attention-deficit hyperactive disorder. *PubMed, 42*(1), 44–48.
- Yusof, M. Y. P. M., Teo, C. H., & Ng, C. J. (2022). Electronic informed consent criteria for research ethics review: A scoping review.
- Zainuddin, Z., & Judi, H. M. (2022). Investigating AI-powered tutoring systems that adapt to individual student needs, providing personalized guidance and assessments. *The Eurasia Proceedings of Educational and Social Sciences, 31*, 67–73.
- Zentall, S. S. (2005). Theory- and evidence-based strategies for children with attentional problems. *Psychology in the Schools, 42*(8), 821–836. https://doi.org/10.1002/pits.20114

- Zhang, M., & Vallabhajosyula, R. (2022). An emotional bias modification for children with attention-deficit/hyperactivity disorder: Co-design study. *JMIR Formative Research, 6*(12), e36390. https://doi.org/10.2196/36390
- Zhang, M., Vallabhajosyula, R., & Fung, D. (2020). Emotional bias modification for individuals with attention deficit hyperactivity disorder: Protocol for a co-design study. *JMIR Research Protocols, 9*(12), e24078. https://doi.org/10.2196/24078
- Zhang, P. (2006). Pop-up animations: Impacts and implications for website design and online advertising. *SSRN Electronic Journal*.
- Zhang, S., & Hu, Q. (2024). NLP-based personal learning assistant for school education. *International Journal of Electrical and Computer Engineering (IJECE), 11*(5), 4522–4530.
- Zhao, S., Hai, G., & Ma, H. (2024). Adaptive learning systems: Exploring personalized paths in vocational education. *Contemporary Logistics and Education, 2*(2). https://doi.org/10.18686/cle.v2i2.3803
- Zhu, Y. (2024). The impact of AI-assisted teaching on students' learning and psychology. *Journal of Education Humanities and Social Sciences, 38*, 111–116. https://doi.org/10.54097/k7a37d11

Appendixes

Appendix A: System Architecture

Jabari's system architecture consists of four components: the frontend, backend logic, LLM core, and database. These components work together to provide an adaptive learning environment tailored to its users.

The **frontend** is built using Next.js, a React framework, and is styled with Tailwind CSS. The combination provides users with a responsive user interface accessible through web browsers. Furthermore, the frontend provides a home page, a learn page, a quiz page, and a profile page. The adaptive tutor runs on the learn page, where the frontend provides a chat-based interface for its users to interact with Jabari.

The **backend logic** consists of several API routes that enable the system to send requests to its main AI engine, Google's Gemini 2.0 Flash. This model serves as the system's **LLM core** and handles the application's natural language processing (NLP), with the model being capable of understanding human input and providing responses through natural language generation (NLG). This allows the user to interact with the chatbot in the learn page in an organic, human-like manner. Furthermore, the backend consists of several routes and operations that handle trait analysis and prompt generation, two key components, further explained in section 3.4.

The **database** employs Google's Firebase Firestore, a NoSQL cloud-based solution, to store its data. This allows for real-time storage of all user data collected throughout the experiment, including pseudonymised user profiles that collect dynamic trait scores, interaction metrics (e.g. response times), survey responses and test scores.

Appendix B: Trait formulas

This appendix lists the quantitative formulas used to calculate scores for the nine personality traits based on user response metrics in the Jabari adaptive tutoring system. As defined in section 3.4.1, the metrics shown in the formulas represent the following:

- **Word Count**: The number of words in the user's response.
- **Response Time**: The time taken to submit a response.
- **Correctness**: A yes/no indicator of whether the response answers a question correctly.
- **Relevance**: A score (0–1) estimating how closely the response aligns with the current learning topic.
- **Consecutive**: The number of consecutive correct or incorrect answers.
- **Off-topic**: A yes/no flag for responses unrelated to the task.
- **Typos**: The count of spelling errors in the response.
- **Attempts**: The number of tries taken for a specific word or concept.
- **Session** Duration: The total time spent in the current session.

Formulas

Trait: Inattention

```python
capScore((
  (offtopic ? 8 : 0) +
  (-5 * relevance + 5) +
  (responseTime > 40 ? 5 : responseTime > 20 ? 2 : 0) +
  (typos * 1.5)
) * (sessionDuration > 20 ? 1.3 : 1))
```

Description:

- ➢ Adds 8 if the response is off-topic (offtopic = true).
- ➢ Scales relevance inversely (-5 * relevance + 5), so lower relevance increases inattention.
- ➢ Adds 5 if response time exceeds 40 seconds, or 2 if it exceeds 20 seconds.
- ➢ Adds 1.5 per typo.
- ➢ Multiplies the sum by 1.3 if session duration exceeds 20 minutes, otherwise by 1.
- ➢ Caps the final score between 1 and 10.

Literature: Forster, S., et al. (2013)

Trait: Frustration

```python
capScore((
  (attempts > 3 ? 7 : attempts * 2) +
  (consecutive < 0 ? -consecutive * 2 : 0) +
  (typos > 3 ? 4 : 0) +
  (!correctness && attempts > 1 ? 3 : 0)
) * (responseTime > 30 ? 1.2 : 1))
```

Description:

- ➢ Adds 7 if attempts exceed 3, otherwise adds 2 * attempts.
- ➢ Adds -2 * consecutive if consecutive streak is negative (incorrect answers), otherwise 0.
- ➢ Adds 4 if typos exceed 3.
- ➢ Adds 3 if the response is incorrect (!correctness) and attempts exceed 1.
- ➢ Multiplies the sum by 1.2 if response time exceeds 30 seconds, otherwise by 1.
- ➢ Caps the final score between 1 and 10.

Literature: Shaw, P., et al. (2014)

Trait: Confidence

```Python
capScore((
  (consecutive > 0 ? consecutive * 2.5 : -2) +
  (responseTime < 10 && correctness ? 3 : -1) +
  (typos === 0 && correctness ? 2 : -typos) +
  (correctness ? 3 : -3)
) * (correctness ? 1.2 : 0.7))
```

Description:

- Adds 2.5 * consecutive if consecutive streak is positive (correct answers), otherwise -2.
- Adds 3 if response time is under 10 seconds and the response is correct, otherwise -1.
- Adds 2 if there are no typos and the response is correct, otherwise subtracts 1 per typo.
- Adds 3 if the response is correct, otherwise subtracts 3.
- Multiplies the sum by 1.2 if the response is correct, otherwise by 0.7.
- Caps the final score between 1 and 10.

Literature: Sailer, M., et al. (2017)

Trait: Sloppiness

```Python
capScore(
  (typos * 2.5) +
  (responseTime < 3 && wordCount < 5 ? 6 : 0) +
  (wordCount < 2 ? 4 : 0) +
  (relevance < 0.3 ? 4 : 0)
)
```

Description:

- Adds 2.5 * typos for each typo.
- Adds 6 if response time is under 3 seconds and word count is under 5.
- Adds 4 if word count is under 2.
- Adds 4 if relevance is below 0.3.
- Caps the final score between 1 and 10.

Literature: Barkley, R. A. (2015)

Trait: Engagement

```Python
capScore(
  (relevance * 7) +
```

```
  (wordCount > 10 ? 4 : wordCount > 5 ? 2 : 0) +
  (attempts > 1 && correctness ? 2 : -1) +
  (!offtopic ? 3 : -5)
)
```

Description:

- ➢ Adds 7 * relevance as the primary factor.
- ➢ Adds 4 if word count exceeds 10, or 2 if it exceeds 5.
- ➢ Adds 2 if attempts exceed 1 and the response is correct, otherwise -1.
- ➢ Adds 3 if the response is not off-topic, otherwise -5.
- ➢ Caps the final score between 1 and 10.

Literature: Whirley, K. S., et al. (2003)

Trait: Boredom

```Python
capScore((
  (responseTime > 25 ? 5 : responseTime > 15 ? 2 : 0) +
  (wordCount < 3 && relevance < 0.5 ? 5 : 0) +
  (sessionDuration > 15 ? 3 : 0) +
  (attempts === 1 && !correctness ? 3 : -1)
) * (consecutive < 0 ? 1.3 : 1))
```

Description:

- ➢ Adds 5 if response time exceeds 25 seconds, or 2 if it exceeds 15 seconds.
- ➢ Adds 5 if word count is under 3 and relevance is below 0.5.
- ➢ Adds 3 if session duration exceeds 15 minutes.
- ➢ Adds 3 if there is only 1 attempt and the response is incorrect, otherwise -1.
- ➢ Multiplies the sum by 1.3 if consecutive streak is negative, otherwise by 1.
- ➢ Caps the final score between 1 and 10.

Literature: Volkow, N. D., et al. (2011)

Trait: Motivation

```Python
capScore((
  (consecutive > 0 ? consecutive * 2.5 : -1) +
  (attempts > 1 ? 3 : 0) +
  (wordCount > 8 ? 3 : wordCount > 4 ? 1.5 : 0) +
```

```
  (relevance * 5) +
  (correctness ? 2 : -2)
) * (sessionDuration > 20 ? 0.8 : 1))
```

Description:

- ➢ Adds 2.5 * consecutive if consecutive streak is positive, otherwise -1.
- ➢ Adds 3 if attempts exceed 1.
- ➢ Adds 3 if word count exceeds 8, or 1.5 if it exceeds 4.
- ➢ Adds 5 * relevance.
- ➢ Adds 2 if the response is correct, otherwise -2.
- ➢ Multiplies the sum by 0.8 if session duration exceeds 20 minutes, otherwise by 1.
- ➢ Caps the final score between 1 and 10.

Literature: Ventouri, E. (2020)

Trait: Impulsivity

```python
capScore(
  (responseTime < 2 ? 8 : responseTime < 5 ? 4 : 0) +
  (offtopic ? 7 : 0) +
  (typos * 2) +
  (wordCount < 2 && relevance < 0.4 ? 4 : 0)
)
```

Description:

- ➢ Adds 8 if response time is under 2 seconds, or 4 if under 5 seconds.
- ➢ Adds 7 if the response is off-topic.
- ➢ Adds 2 * typos for each typo.
- ➢ Adds 4 if word count is under 2 and relevance is below 0.4.
- ➢ Caps the final score between 1 and 10.

Literature: Malloy-Diniz, L., et al. (2007)

Trait: Fatigue

```python
capScore((
  (sessionDuration > 20 ? 5 : sessionDuration > 10 ? 2 : 0) +
  (responseTime > 30 ? 4 : responseTime > 20 ? 2 : 0) +
  (wordCount < 4 ? 3 : 0) +
```

```
  (consecutive < -2 ? 4 : 0)
) * (consecutive < -1 ? 1.4 : 1))
```

Description:

- ➢ Adds 5 if session duration exceeds 20 minutes, or 2 if it exceeds 10 minutes.
- ➢ Adds 4 if response time exceeds 30 seconds, or 2 if it exceeds 20 seconds.
- ➢ Adds 3 if word count is under 4.
- ➢ Adds 4 if consecutive streak is less than -2 (multiple incorrect answers).
- ➢ Multiplies the sum by 1.4 if consecutive streak is less than -1, otherwise by 1.
- ➢ Caps the final score between 1 and 10.

Literature: Barkley, R. A. (2015)

Appendix C: Off-topic questions

- 'What was your last holiday location? Tell me a bit about it.',
- 'Describe a favourite hobby or activity you enjoy.',
- 'What's a book or movie you recently enjoyed? Why?',
- 'If you could have any superpower, what would it be and why?',
- 'What is one skill you would like to learn or improve?',
- 'Tell me about a place you would love to visit one day.',
- 'What is something that made you smile recently?',
- 'If you could meet any historical figure, who would it be?',
- 'What is your favourite type of music or a favourite song?',
- 'Describe your ideal weekend.'

Appendix D: Trait-specific Prompt

The following list shows the additions that are made to prompt instructions when the system selects a trait and selects its corresponding score.

<u>**Trait: Inattention**</u>
threshold: minimal (0–2)
instructions:

- "Use short, concise sentences to present content clearly."
- "Highlight key terms in bold to capture attention."
- "Ask a simple, engaging question to reinforce the topic."
- "Provide a single visual cue (e.g., an icon) to anchor focus."
- "Maintain a steady pace to avoid overwhelming the user."

literature: Salomone et al. (2016); Zentall (2005)

threshold: low (2–4)

- "Break content into small, digestible chunks to support focus."
- "Use direct, simple questions to check comprehension."
- "Emphasize one key concept per interaction in bold."
- "Remind the user of the task's goal to maintain focus."
- "Include a quick yes/no question to sustain engagement."

literature: Salomone et al. (2016); Kusumasari et al. (2018)

threshold: moderate (4–6)

- "Provide one clear instruction at a time to reduce distraction."
- "Repeat key points to reinforce attention."
- "Pause briefly to ask if the user is following along."
- "Use visual emphasis (e.g., bold text) for critical content."
- "Suggest a keyword to anchor attention to the main idea."

literature: Salomone et al. (2016); Forster et al. (2013)

threshold: high (6–8)

- "Reduce content to only essential information."
- "Use highly engaging, interactive prompts to recapture focus."
- "Provide immediate, concise feedback to keep on track."
- "Offer a single, clear task to minimize distractions."
- "Include a motivational phrase to encourage sustained attention."

literature: Salomone et al. (2016); Zentall (2005)

threshold: very high (8–10)

- "Limit to one simple, clear instruction per interaction."
- "Use strong visual cues (e.g., bold, large text) for key content."
- "Ask a quick check-in question to redirect focus."
- "Suggest a brief pause or refocusing strategy (e.g., 'Take a deep breath')."
- "Provide positive reinforcement to sustain effort."

literature: Salomone et al. (2016); Kusumasari et al. (2018)

Trait: Frustration

threshold: minimal (0–2)

- "Use a calm, supportive tone in all responses."
- "Provide clear, positive feedback for correct answers."

- "Offer an encouraging phrase to boost confidence."
- "Keep tasks straightforward to prevent frustration."
- "Show a simple progress indicator to highlight advancement."

literature: Shaw et al. (2014); Knouse et al. (2011)

threshold: low (2–4)
- "Acknowledge effort with specific, positive feedback."
- "Simplify the current task to reduce perceived difficulty."
- "Use an empathetic tone (e.g., ‘Let’s make this easier together’)."
- "Provide a quick, easy question to build momentum."
- "Remind the user of progress to maintain motivation."

literature: Shaw et al. (2014); Morris et al. (2023)

threshold: moderate (4–6)
- "Break tasks into smaller, manageable steps."
- "Use empathetic language (e.g., ‘This can be tricky, let’s try it together’)."
- "Provide immediate, constructive feedback to guide improvement."
- "Offer a choice between two simple tasks to enhance autonomy."
- "Reinforce progress with a positive comment."

literature: Shaw et al. (2014); González-Sánchez et al. (2019)

threshold: high (6–8)
- "Simplify content to reduce overwhelm."
- "Use a highly supportive tone (e.g., ‘You’re doing great, let’s take it slow’)."
- "Provide a single, clear task to focus effort."
- "Offer a motivational prompt to reduce stress."
- "Suggest a brief break if frustration persists."

literature: Shaw et al. (2014); Wu et al. (2020)

threshold: very high (8–10)
- "Let's break this down into very small, clear steps."
- "Focus on the most important part of the current information. You can bold it."
- "We'll ignore other details for now."
- "Ask a quick check-in question about what was just covered."
- "Suggest a simple visual anchor or keyword for the main idea."

literature: Shaw et al. (2014); González-Sánchez et al. (2019)

Trait: Confidence

threshold: minimal (0–2)

- "Provide frequent, specific praise for any effort or progress."
- "Set very small, achievable tasks to ensure success."
- "Use positive language to boost self-efficacy (e.g., 'You're capable of this!')."
- "Highlight a recent success to reinforce capability."
- "Ask a simple question to build confidence."

literature: Knouse et al. (2011); Sailer et al. (2016)

threshold: low (2–4):

- "Emphasize effort with tangible, positive feedback."
- "Break tasks into small steps to ensure success."
- "Use affirming phrases (e.g., 'You've got this!')."
- "Show a clear progress indicator to reinforce achievement."
- "Ask a straightforward question to build competence."

literature: Knouse et al. (2011); Morris et al. (2023)

threshold: moderate (4–6)

- "Provide balanced feedback acknowledging effort and suggesting improvement."
- "Set moderately challenging tasks to stretch ability."
- "Use encouraging language to maintain momentum."
- "Show progress visually to reinforce achievement."
- "Ask a question that builds on prior success."

literature: Knouse et al. (2011); Sailer et al. (2016)

threshold: high (6–8)

- "Offer praise for specific achievements to sustain confidence."
- "Introduce slightly more complex tasks to maintain engagement."
- "Use positive language to reinforce self-efficacy."
- "Provide a progress update to highlight ongoing success."
- "Ask a question that encourages reflection on achievements."

literature: Knouse et al. (2011); Morris et al. (2023)

threshold: very high (8–10)

- "Celebrate achievements with enthusiastic feedback."
- "Introduce challenging tasks to leverage high confidence."
- "Use empowering language (e.g., 'You're excelling at this!')."
- "Show detailed progress to reinforce mastery."
- "Ask a reflective question to deepen engagement."

literature: Knouse et al. (2011); Sailer et al. (2016)

Trait: Sloppiness

threshold: minimal (0–2)

- "Provide clear, structured instructions to promote accuracy."
- "Use examples to clarify expected responses."
- "Offer gentle feedback on minor errors to encourage precision."
- "Highlight correct responses to reinforce careful work."
- "Ask a simple question to focus on detail."

  literature: Barkley (2015); Knouse et al. (2011)

threshold: low (2–4)

- "Break tasks into clear, step-by-step instructions."
- "Provide specific feedback on errors to guide improvement."
- "Use visual cues (e.g., **bold** text) to emphasize key details."
- "Encourage the user to double-check their response."
- "Ask a question that requires attention to detail."

literature: Barkley (2015); Kusumasari et al. (2018)

threshold: moderate (4–6)

- "Simplify tasks to focus on accuracy over speed."
- "Provide immediate feedback on errors with clear corrections."
- "Use structured prompts to guide precise responses."
- "Remind the user to take their time on the task."
- "Ask a question with clear, specific expectations."

literature: Barkley (2015); Knouse et al. (2011)

threshold: high (6–8)

- "Reduce task complexity to emphasize accuracy."
- "Provide detailed feedback on errors with step-by-step guidance."
- "Use strong visual cues to highlight critical details."
- "Encourage a slow, deliberate approach to the task."
- "Ask a simple, detail-oriented question to refocus."

literature: Barkley (2015); Kusumasari et al. (2018)

threshold: very high (8–10)

- "Limit tasks to one clear, simple step to ensure accuracy."
- "Provide immediate, corrective feedback with examples."
- "Use **bold** text and visual anchors for essential details."

- "Prompt the user to review their response before submitting."
- "Ask a highly structured question to minimize errors."

literature: Barkley (2015); Knouse et al. (2011)

<u>Trait: Engagement</u>
threshold: minimal (0–2)
- "Use highly interactive prompts to spark interest."
- "Incorporate a fun, engaging question to draw attention."
- "Provide positive feedback to encourage participation."
- "Relate content to the user’s interests where possible."
- "Use a lively tone to boost engagement."

literature: Sailer et al. (2016); Whirley et al. (2003)

threshold: low (2–4)
- "Introduce an interactive element, like a quick quiz."
- "Provide enthusiastic feedback to sustain interest."
- "Ask a question that connects to real-world applications."
- "Use visual cues to highlight engaging content."
- "Offer a motivational phrase to spark interest."

literature: Sailer et al. (2016); Plaza Casado et al. (2020)

threshold: moderate (4–6)
- "Maintain engagement with varied, interactive prompts."
- "Provide positive feedback tied to specific actions."
- "Ask a question that encourages creative thinking."
- "Show progress to reinforce participation."
- "Use an upbeat tone to sustain interest."

literature: Sailer et al. (2016); Whirley et al. (2003)

threshold: high (6–8)
- "Introduce slightly more complex, engaging tasks."
- "Provide enthusiastic praise for active participation."
- "Ask a question that builds on the user’s interests."
- "Use dynamic visual cues to maintain focus."
- "Encourage continued engagement with positive reinforcement."

literature: Sailer et al. (2016); Plaza Casado et al. (2020)

threshold: very high (8–10)
instructions:

- "Offer highly interactive, challenging tasks to sustain engagement."
- "Celebrate participation with enthusiastic feedback."
- "Ask a creative, open-ended question to deepen involvement."
- "Show detailed progress to highlight engagement."
- "Use a lively, encouraging tone to maintain enthusiasm."

literature: Sailer et al. (2016); Whirley et al. (2003)

Trait: Boredom

threshold: minimal (0–2)

- "Maintain a varied, engaging pace in interactions."
- "Introduce an interesting, relevant question to spark curiosity."
- "Provide positive feedback to sustain interest."
- "Use a lively tone to keep the session dynamic."
- "Relate content to the user’s interests where possible."

literature: Volkow et al. (2010); Sailer et al. (2016)

threshold: low (2–4)

- "Introduce a fun, interactive element to counter boredom."
- "Ask a question that connects to real-world scenarios."
- "Provide enthusiastic feedback to boost interest."
- "Use visual cues to highlight engaging content."
- "Offer a motivational phrase to maintain attention."

literature: Volkow et al. (2010); Plaza Casado et al. (2020)

threshold: moderate (4–6)

- "Vary task types to sustain interest."
- "Ask an engaging, creative question to spark curiosity."
- "Provide positive feedback tied to specific actions."
- "Use dynamic visual cues to maintain focus."
- "Encourage participation with an upbeat tone."

literature: Volkow et al. (2010); Sailer SPE et al. (2016)

threshold: high (6–8)

- "Introduce highly engaging, interactive tasks to counter boredom."
- "Ask a question that encourages creative or personal input."
- "Provide enthusiastic feedback to rekindle interest."
- "Use strong visual cues to highlight key content."
- "Suggest a quick, fun activity to reset focus."

literature: Volkow et al. (2010); Plaza Casado et al. (2020)

threshold: very high (8–10)

- "Offer a highly interactive, novel task to combat boredom."
- "Ask an open-ended, engaging question to spark interest."
- "Provide enthusiastic, specific feedback to rekindle motivation."
- "Use bold visual cues to anchor attention."
- "Suggest a brief, fun break activity to refresh focus."

literature: Volkow et al. (2010); Sailer et al. (2016)

Trait: Motivation

threshold: minimal (0–2)

- "Set very small, easily achievable goals to build momentum."
- "Use frequent, tangible praise for effort and completion."
- "Break tasks into small steps to reduce perceived effort."
- "Gently remind the user of the benefits of learning."
- "Ask a simple question to encourage progress."

literature: Volkow et al. (2010); Morris et al. (2023)

threshold: low (2–4)

- "Set very small, easily achievable goals to build momentum."
- "Use frequent, tangible praise for effort and completion."
- "Break tasks down to reduce perceived effort."
- "Gently remind them of the benefits or relevance of learning."
- "Ask a quick, motivating question to sustain effort."

literature: Volkow et al. (2010); Morris et al. (2023)

threshold: moderate (4–6)

- "Set moderately challenging goals to maintain motivation."
- "Provide specific, positive feedback for progress."
- "Break tasks into clear, manageable steps."
- "Connect content to real-world applications to boost relevance."
- "Ask a question that encourages reflection on progress."

literature: Volkow et al. (2010); Sailer et al. (2016)

threshold: high (6–8)

- "Introduce slightly more challenging tasks to sustain motivation."
- "Provide enthusiastic praise for achievements."
- "Highlight progress to reinforce a sense of accomplishment."
- "Relate tasks to personal goals or interests."
- "Ask a question that builds on current motivation."

literature: Volkow et al. (2010); Morris et al. (2023)

threshold: very high (8–10)
- "Offer challenging tasks to leverage high motivation."
- "Celebrate progress with enthusiastic, specific feedback."
- "Connect content to long-term goals or interests."
- "Show detailed progress to reinforce mastery."
- "Ask an open-ended question to deepen engagement."

literature: Volkow et al. (2010); Sailer et al. (2016)

Trait: Impulsivity
threshold: minimal (0–2)
- "Provide clear, structured prompts to guide responses."
- "Use gentle reminders to focus on the current task."
- "Offer positive feedback for deliberate, thoughtful answers."
- "Ask a simple, focused question to maintain control."
- "Use visual cues to anchor attention to the task."

literature: Fernandes Malloy-Diniz et al. (2007); Barkley (2015)

threshold: low (2–4)
- "Break tasks into clear, single-step instructions."
- "Provide immediate feedback to encourage thoughtful responses."
- "Use **bold** text to emphasize key instructions."
- "Remind the user to take their time before responding."
- "Ask a question that requires careful consideration."

literature: Fernandes Malloy-Diniz et al. (2007); Knouse et al. (2011)

threshold: moderate (4–6)
- "Simplify tasks to promote deliberate responses."
- "Provide specific feedback to guide controlled behavior."
- "Use structured prompts to minimize rushed answers."
- "Encourage a pause before responding to questions."
- "Ask a question with clear, specific expectations."

literature: Fernandes Malloy-Diniz et al. (2007); Barkley (2015)

threshold: high (6–8)
- "Reduce task complexity to encourage careful responses."
- "Provide immediate, corrective feedback for rushed answers."
- "Use strong visual cues to focus attention."
- "Prompt the user to review their response before submitting."

- "Ask a highly structured, single-focus question."

literature: Fernandes Malloy-Diniz et al. (2007); Knouse et al. (2011)

threshold: very high (8–10)
- "Limit tasks to one clear, simple step to control impulsivity."
- "Provide detailed feedback with examples for correct responses."
- "Use **bold**, large text to anchor attention."
- "Encourage a deliberate, slow approach to answering."
- "Ask a simple, highly structured question to minimize errors."

literature: Fernandes Malloy-Diniz et al. (2007); Barkley (2015)

<u>Trait: Fatigue</u>
threshold: minimal (0–2)
- "Maintain a steady, manageable pace for tasks."
- "Provide positive feedback to sustain energy."
- "Break content into small, clear segments."
- "Ask a simple, low-effort question to maintain engagement."
- "Use an encouraging tone to boost energy."

literature: Kusumasari et al. (2018); Barkley (1997)

threshold: low (2–4)
- "Simplify tasks to reduce mental effort."
- "Provide frequent, positive feedback to sustain effort."
- "Use short, clear prompts to minimize strain."
- "Ask a quick, easy question to keep engagement."
- "Offer a motivational phrase to boost energy."

literature: Kusumasari et al. (2018); Knouse et al. (2011)

threshold: moderate (4–6)
- "Reduce task complexity to conserve mental energy."
- "Provide supportive feedback to encourage persistence."
- "Use concise prompts to minimize cognitive load."
- "Ask a low-effort question to maintain focus."
- "Suggest a brief mental reset (e.g., ‘Take a moment to breathe’)."

literature: Kusumasari et al. (2018); Barkley (1997)

threshold: high (6–8)
- "Limit tasks to essential, low-effort activities."
- "Provide empathetic feedback to acknowledge effort."

- "Use very short, clear prompts to reduce strain."
- "Ask a simple question to sustain minimal engagement."
- "Suggest a short break to refresh focus."

literature: Kusumasari et al. (2018); Knouse et al. (2011)

threshold: very high (8–10)
- "Offer one minimal-effort task to avoid overwhelm."
- "Use highly supportive, empathetic feedback."
- "Provide ultra-concise prompts with **bold** key points."
- "Ask a very simple check-in question to maintain contact."
- "Suggest a brief break or refocusing activity."

literature: Kusumasari et al. (2018); Barkley (1997)

Appendix E: Gemini Prompt Build

```python
const promptText = `You are Jabari, a patient Swahili tutor for adults with ADHD. Your goal is to deliver a concise, engaging message or question based on the Core Task.

Guidelines:

Base:
- Maintain a supportive, encouraging tone.
- Bold **Swahili words** and *italicize* translations for emphasis.
- Make sure that the responses are organic and human-like, not robotic or overly structured.
- Only use Swahili words from specified word list.

Core Task: ${input.experimentState}
- For new words, state the Swahili word and its english meaning first, then ask a related question.
- For initial greetings, welcome the user, teach the first word, and ask a related question.
- Acknowledge the user's input if they provide a response.
- Only use Swahili words from specified word list.
- Only ask users to create sentences in Level 4. For Levels 1-3, focus on word recognition, meanings, and basic concepts.
- Only use the Swahili words with their assigned meanings (so do never say jua means "sun" first, and then "know" second)

Specific Guidance (the following is only if specific instructions are inputted): ${input.specificInstructions}
- Use clear, short sentences in digestible chunks.
- Apply Specific Guidance to adjust tone and style (e.g., simpler for high inattention).
- For continuing words, acknowledge prior input briefly (without literally saying "you said ...", tell them you agree or give a thought) and ask a new question about the word's meaning or use.
- If the user says something off-topic or asks an unrelated question, answer it shortly, then smoothly transition back to our Swahili lesson or the current Core Task.
```

Appendix F: Questionnaire

Section 1: About You

1. **Age:** _____ years

2. **Nationality:** (Open text box) _____________

3. **Primary Language(s) spoken:** (Open text box) _____________

4. **Highest Level of Education Completed:**
   ○ [ ] High School / Secondary School
   ○ [ ] Vocational Training
   ○ [ ] Bachelor's Degree
   ○ [ ] Master's Degree
   ○ [ ] Doctoral Degree
   ○ [ ] Other: _____________

5. **Have you received a formal diagnosis of ADHD from a qualified professional?**
   ○ [ ] Yes
   ○ [ ] No
   ○ [ ] Prefer not to say

6. **Which type of ADHD are you diagnosed with?**
   ○ [ ] ADHD hyperactive/impulsive type
   ○ [ ] ADHD inattentive type (for some known as ADD)
   ○ [ ] ADHD combined type (most common type)
   ○ [ ] I am not sure
   ○ [ ] I am not diagnosed with ADHD *(Note: Consider how this interacts with Q5, especially if Q5 is a screening criterion.)*

Section 2: Your Experience with the Learning Session (Likert Scales)

Please rate your agreement with the following statements based on the Swahili learning session you just completed with the chatbot. Use the scale: 1 = Strongly Disagree 2 = Disagree 3 = Neutral 4 = Agree 5 = Strongly Agree

7. **The chatbot helped me stay focused on the learning task.** [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

8. **I found the learning session engaging.** [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

9. **The instructions provided by the chatbot were clear and easy to understand.** [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

10. **The pace of the learning session was appropriate for me.** [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

11. **I feel I learned some basic Swahili during this session.** [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

12. **The way the chatbot presented information was easy to follow.** [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

13. **I felt motivated throughout most of the learning session.** [ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] 5

Section 3: Perceived Workload (NASA-TLX)

The following questions ask you to rate the workload you experienced during the Swahili learning session with the chatbot. For each scale, please indicate the level of workload you experienced by selecting a point on the scale from 0 to 100.

14. **Mental Demand:** How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching)? Was the task easy or demanding, simple or complex, exacting or forgiving? *Scale: 0 (Very Low) to 100 (Very High)* Value (0-100): _____
15. **Physical Demand:** How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating)? Was the task easy or demanding, slow or brisk, slack or strenuous, restful or laborious? *(Note: Physical Demand is often low for computer-based tasks. Please rate appropriately.) Scale: 0 (Very Low) to 100 (Very High)* Value (0-100): _____

16. **Temporal Demand:** How much time pressure did you feel due to the rate or pace at which the tasks or task elements occurred? Was the pace slow and leisurely or rapid and frantic? *Scale: 0 (Very Low) to 100 (Very High)* Value (0-100): _____

17. **Performance:** How successful do you think you were in accomplishing the goals of the learning task set by the experimenter (or yourself)? How satisfied were you with your performance in accomplishing these goals? *Scale: 0 (Very Poor / Failure) to 100 (Very Good / Perfect)* Value (0-100): _____

18. **Effort:** How hard did you have to work (mentally and physically) to accomplish your level of performance? *Scale: 0 (Very Low) to 100 (Very High)* Value (0-100): _____

19. **Frustration Level:** How insecure, discouraged, irritated, stressed, and annoyed versus secure, gratified, content, relaxed, and complacent did you feel during the task? *Scale: 0 (Very Low) to 100 (Very High)* Value (0-100): _____

Appendix G: Swahili Test questions

Level 1: Nature Words
Question ID: st1_maji
Type: Multiple-Choice
Question: What does "maji" mean in English?
Options: Water, Rock, Sky, Tree
Answer: Water

Question ID: st2_jua_translate
Type: Open-Ended
Question: Translate "sun" to Swahili.
Answer: jua

Question ID: st3_mlima
Type: Multiple-Choice
Question: What is the Swahili word for "mountain"?
Options: Mlima, Mto, Bahari, Nyasi
Answer: Mlima

Question ID: st4_ndege_translate
Type: Open-Ended
Question: What does "ndege" mean in English?
Answer: bird

Level 2: Animal Words
Question ID: st5_simba
Type: Multiple-Choice
Question: What does "simba" mean in English?
Options: Lion, Tiger, Leopard, Cheetah
Answer: Lion

Question ID: st6_twiga_translate
Type: Open-Ended
Question: Translate "giraffe" to Swahili.
Answer: twiga

Question ID: st7_tembo
Type: Multiple-Choice
Question: The Swahili word "tembo" means:
Options: Elephant, Rhino, Buffalo, Zebra
Answer: Elephant

Question ID: st8_kiboko_translate
Type: Open-Ended
Question: What animal is a "kiboko"?
Answer: hippopotamus

Level 3: Verbs and Grammar
Question ID: st9_ona
Type: Multiple-Choice
Question: What does the verb "ona" mean?
Options: To see, To hear, To smell, To touch
Answer: To see

Question ID: st10_penda_translate
Type: Open-Ended
Question: Translate "to love" into Swahili.
Answer: penda

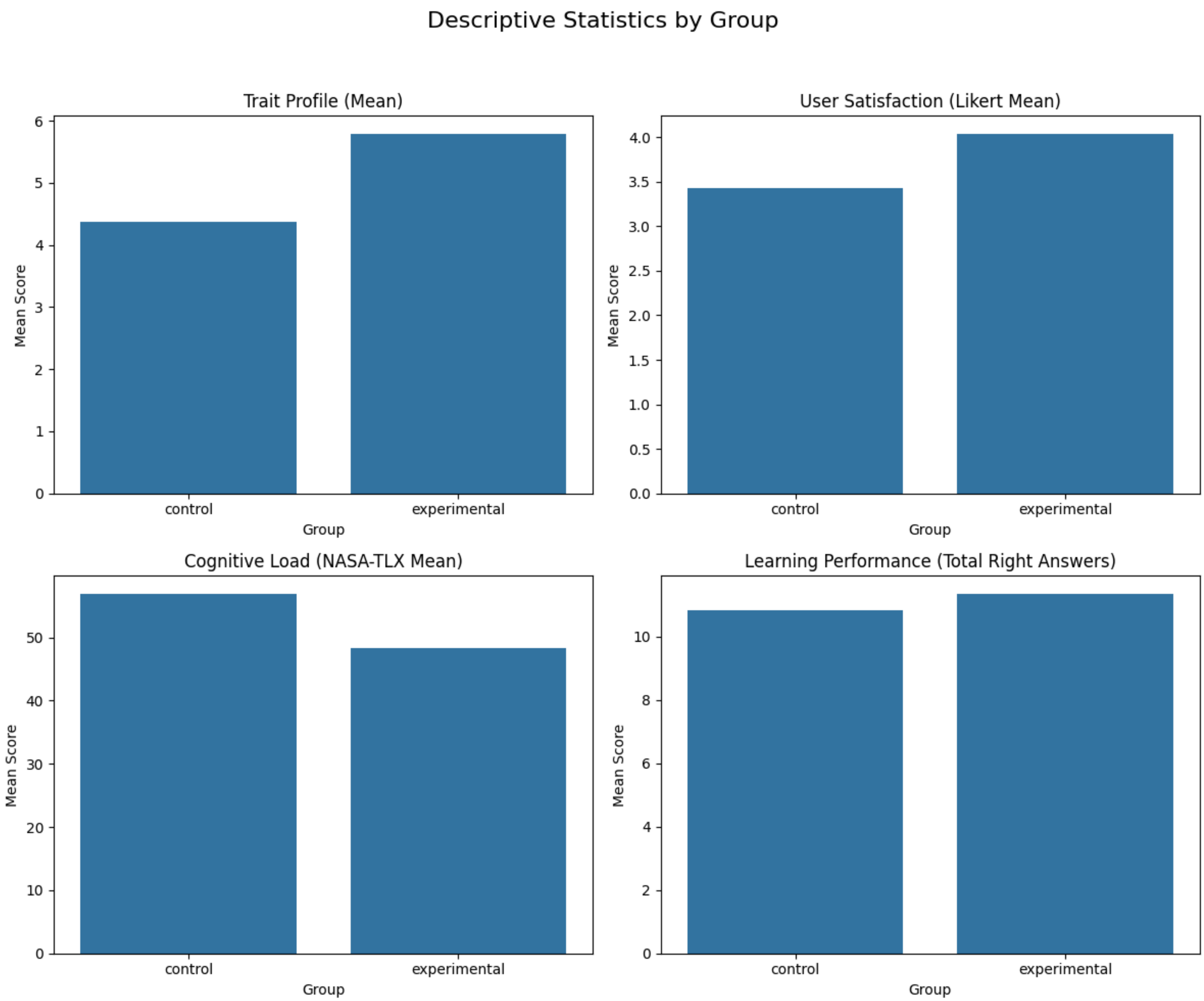
Level 4: Sentence Building
Question ID: st11_sentence1
Type: Multiple-Choice
Question: What is the correct Swahili sentence for "Lion sees bird"?
Options: Simba ona ndege, Ndege ona simba, Simba penda ndege, Ndege penda simba
Answer: Simba ona ndege

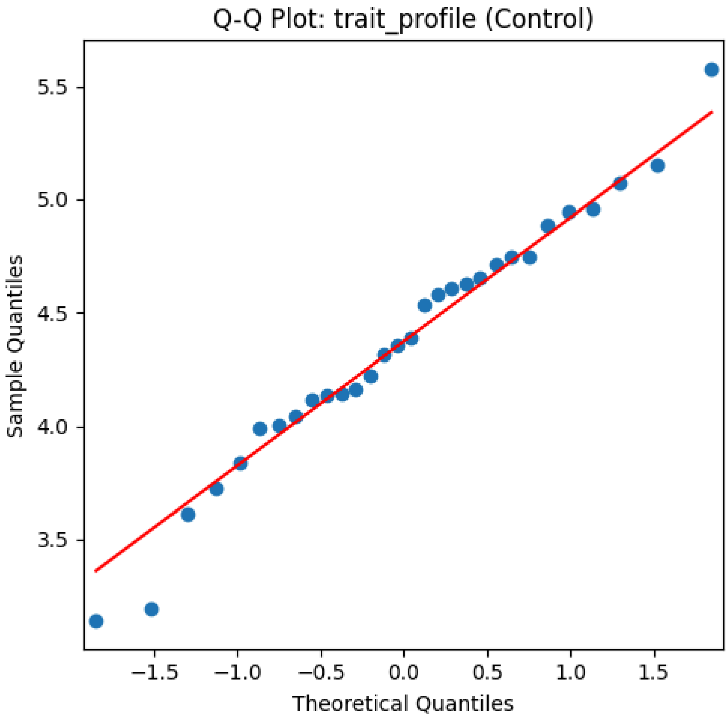
Question ID: st12_sentence2_translate
Type: Open-Ended
Question: Translate "Tembo ona twiga" to English.
Answer: Elephant sees giraffe

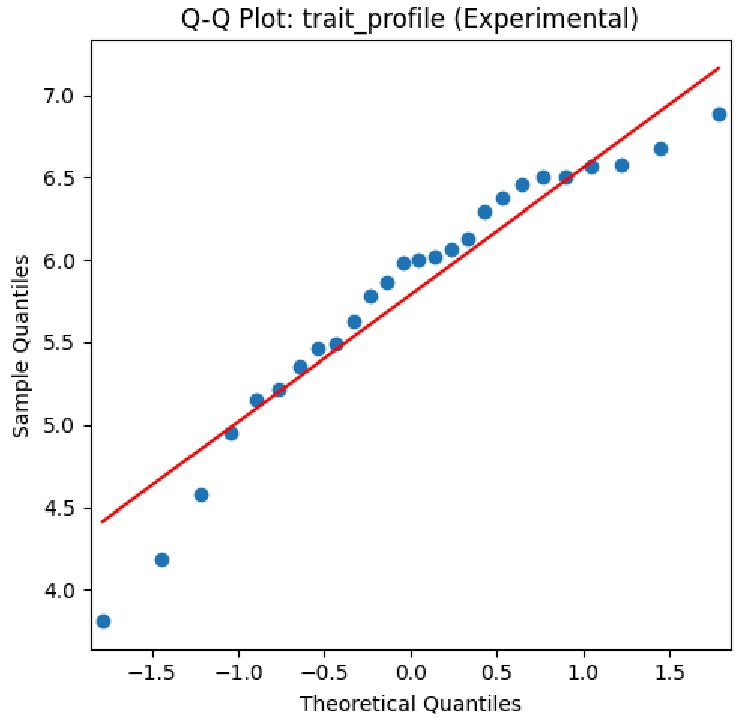
Question ID: st13_sentence_construct
Type: Open-Ended
Question: How would you say "Hippopotamus loves water" in Swahili using the words you learned?
Answer: Kiboko penda maji

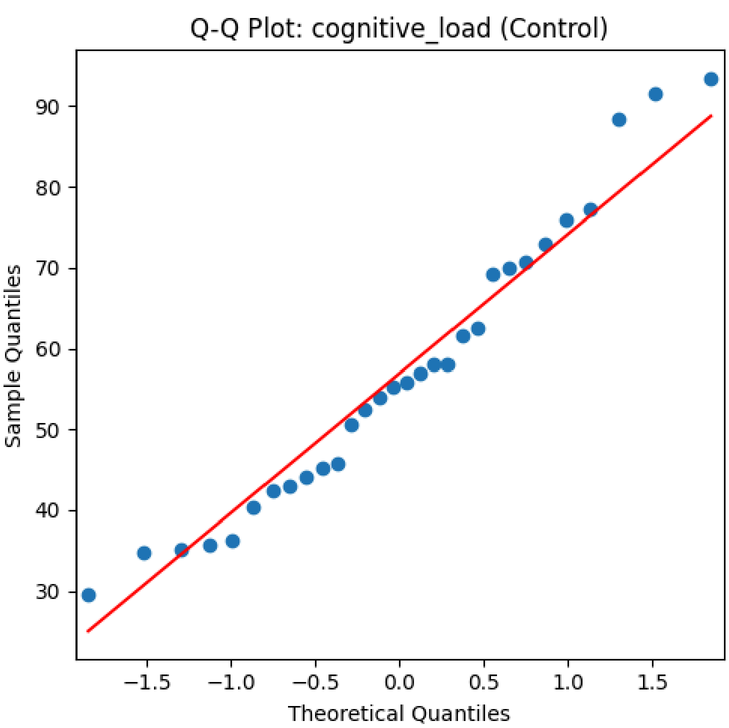
Question ID: st14_sentence_construct2
Type: Open-Ended
Question: Construct a Swahili sentence for "Giraffe sees mountain".
Answer: Twiga ona mlima

Appendix H: Statistical Plots




Q-Q Plot: trait_profile (Control)
Sample Quantiles
Theoretical Quantiles
5.5
5.0
4.5
4.0
3.5
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Q-Q Plot: trait_profile (Experimental)
Sample Quantiles
Theoretical Quantiles
7.0
6.5
6.0
5.5
5.0
4.5
4.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Q-Q Plot: cognitive_load (Control)
Sample Quantiles
Theoretical Quantiles
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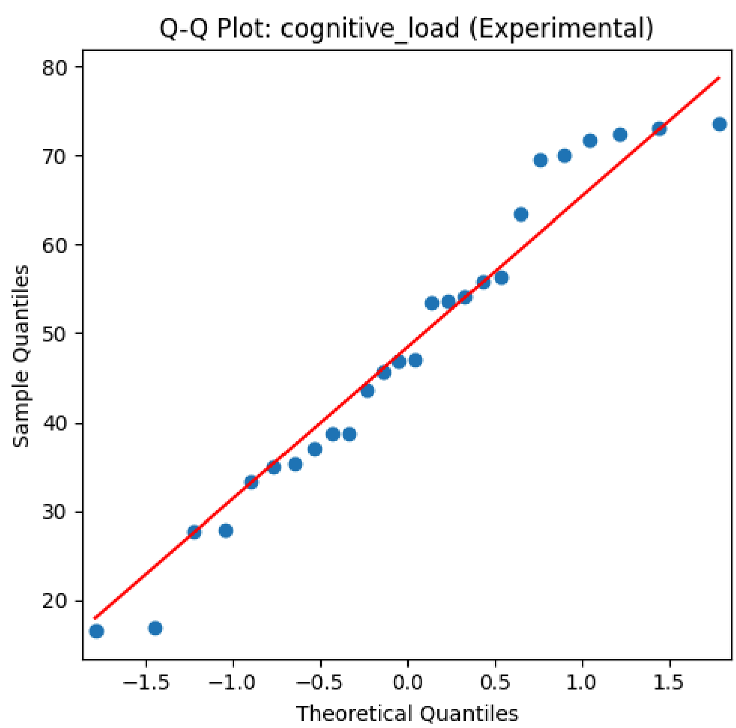
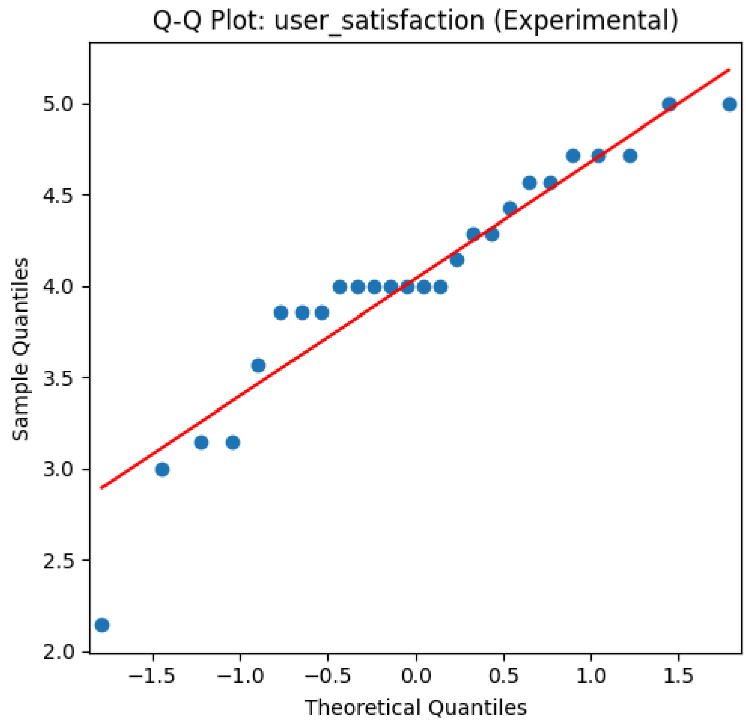
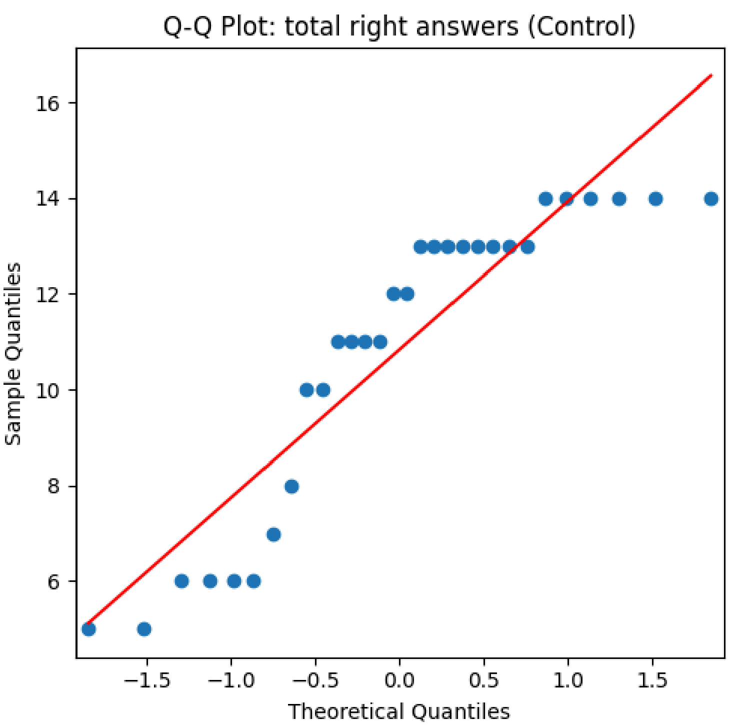
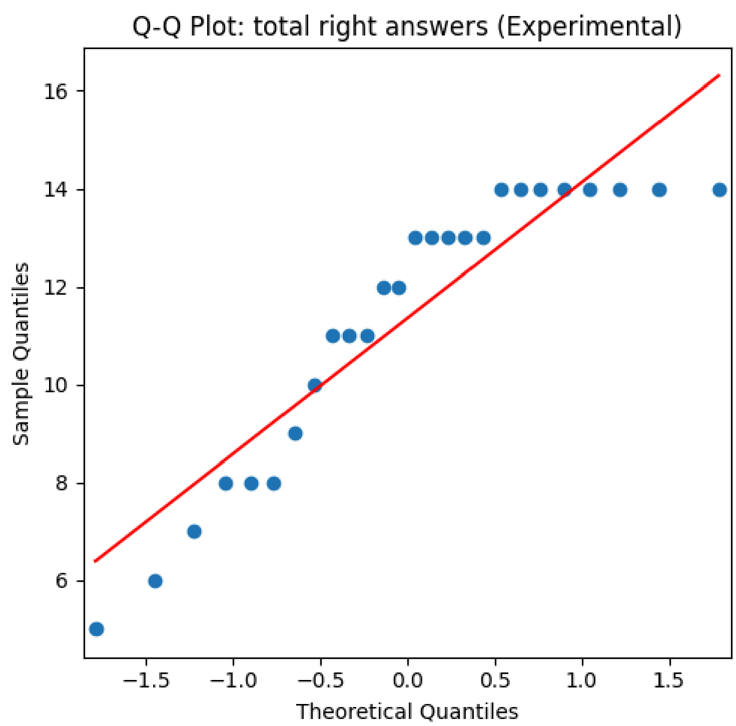
70
60
50
40
30
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Q-Q Plot: cognitive_load (Experimental)
Sample Quantiles
Theoretical Quantiles
80
70
60
50
40
30
20
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5


Q-Q Plot: user_satisfaction (Control)
Sample Quantiles
Theoretical Quantiles


Q-Q Plot: user_satisfaction (Experimental)
Sample Quantiles
Theoretical Quantiles


Q-Q Plot: total right answers (Control)
Sample Quantiles
Theoretical Quantiles


Q-Q Plot: total right answers (Experimental)
Sample Quantiles
Theoretical Quantiles