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Voice or Text? Task Abandonment and Usability Challenges with Voice-Enabled versus Text-Based Generative AI Chatbots Among Students with Academic Difficulties.

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Résumé

Ce mémoire étudie le potentiel de l'IA générative avec la reconnaissance vocale en tant qu'outil pédagogique pour les élèves ayant des difficultés scolaires. Plus précisément, nous cherchons à savoir si les canaux de communication médiatisés par l'IA, en particulier ceux dotés d'une assistance vocale, peuvent soutenir les performances scolaires de ces élèves et répondre à leurs besoins spécifiques en comparaison avec des interactions traditionnelles entre l'enseignant et l'étudiant. Fondée sur le modèle de la richesse des médias et sur la théorie de la présence sociale, l'étude explore l'impact de l'IA générative avec reconnaissance vocale sur les performances, les perceptions et les intentions d'utilisation, en particulier pour les élèves ayant des difficultés scolaires et linguistiques. Les effets sont comparés entre trois modalités : (1) IA générative basée sur le texte, (2) IA générative basée sur la voix et (3) une interaction en ligne synchronisée entre l'élève et l'enseignant.

Ce mémoire utilise une méthode mixte, une conception intra-sujet utilisant une structure factorielle 2x3 pour comparer trois modalités de communication, l'IA générative basée sur le texte, l'IA générative basée sur la voix, et la conversation en ligne à distance avec un enseignant, à travers deux groupes de participants - des élèves avec et sans difficultés scolaires. Les participants ont été recrutés dans une école nord-américaine (Secondaire) et dans un laboratoire d'expérience utilisateur, où ils ont effectué des tâches structurées avec chaque modalité. Après avoir complété chaque tâche, les participants ont rempli un questionnaire évaluant leur satisfaction. À la fin de l'étude, ils ont classé leur expérience globale des différentes modalités en fonction de variables clés telles que la confiance, la confidentialité et l'intention d'utilisation. Les données ont été analysées à l'aide de techniques statistiques, notamment la régression linéaire, la régression logistique et la régression logistique cumulative avec des intercepts aléatoires, afin d'examiner les relations entre le type de média, la performance, les perceptions, la satisfaction et l'intention d'utilisation.

Les résultats révèlent que, bien qu'il n'y ait pas de différence significative dans l'engagement comportemental ou des taux de réussite des tâches entre les trois modalités, le temps de réalisation des tâches était significativement plus court avec les outils d'IA générative qu'avec la conversation à distance avec l'enseignant. Malgré cette efficacité, les élèves ont perçu leur conversation avec l'enseignant comme plus fiable et plus confidentielle. L'engagement comportemental, bien qu'il ne soit pas statistiquement différent, est apparu plus élevé dans les interactions dirigées par l'enseignant, avec un désengagement notable dans les modalités d'IA. Ce désengagement est souvent corrélé au manque de clarté des instructions émises par les élèves ainsi que par l'outil d'IA générative, mais également par un manque de compréhension ou encore par une interprétation erronée des réponses de l'IA générative comme étant des indications que la tâche est complétée. L'IA générative avec assistance vocale a été perçue comme moins fiable et confidentielle que les interactions dirigées par des humains, en particulier par les élèves ayant des difficultés scolaires. L'analyse a également révélé que les taux de réussite des tâches étaient positivement corrélés à la satisfaction des élèves à l'égard du type de média, tandis que les perceptions de la confiance et de la confidentialité ne déterminaient pas significativement la satisfaction. En outre, la satisfaction n'a pas eu d'impact significatif sur l'intention des élèves d'utiliser le média, ce qui suggère que d'autres facteurs peuvent jouer un rôle plus important dans la détermination de leurs préférences.Cette étude contribue à la compréhension du rôle de la richesse des médias et de la présence sociale dans les environnements éducatifs, en soulignant les forces et les limites de l'IA générative avec assistance vocale pour soutenir les élèves ayant des difficultés scolaires. Ces informations sont précieuses pour les éducateurs et les développeurs d'IA qui cherchent à améliorer l'engagement des élèves et les résultats de l'apprentissage par le biais de canaux médiatiques optimisés.

Mots-clés : IA générative, assistance vocale, difficultés scolaires, performances des élèves, expérience utilisateur, richesse des médias, présence sociale, perception, satisfaction, intention d'utilisation.

Abstract

This thesis investigates the potential of generative artificial intelligence (AI) with speech recognition as an educational tool for students with academic difficulties. Here, we examine how AI-mediated communication channels, particularly those with voice assistance, can support the academic performance of these students and address their specific needs compared to traditional teacher-student interactions. Grounded in the Media Richness Model and Social Presence Theory, this study explores how generative AI with speech recognition impacts performance, perceptions of trust and confidentiality, and usage intentions, particularly in students with academic and language difficulties. The effects are compared across three modalities: (1) text-based chat with generative AI, (2) voice-based chat generative AI, and (3) and a text-based chat with teacher.

The study employs a 2x3 factorial design to compare the three communication modalities across two groups: students with academic difficulties (treatment group) and students without academic difficulties (control group). Participants were recruited from a single North American secondary school (junior high school) and a user experience laboratory and completed structured French grammar tasks using each modality. After completing each task, participants filled out a questionnaire to assess their satisfaction. At the end of the study, they ranked their overall experience across modalities based on key variables such as trust, confidentiality, and intention to use. Data were analyzed using linear regression, logistic regression, and cumulative logistic regression with random intercepts to examine the relationships between media type, performance, perceptions, satisfaction, and intention to use.

The findings reveal that while there was no significant difference in behavioral engagement or successful task completion rates across the three modalities, task completion time was significantly shorter with the text-based generative AI tool compared to the text-based chat with the teacher. Despite this efficiency, students perceived the synchronized chat with the teacher as more reliable and confidential. Behavioral engagement, though not statistically different, appeared highest in teacher-led interactions, with noticeable disengagement in AI modalities. This disengagement was often attributed to unclear instructions from both the students and the generative AI tool, as well as misunderstandings, or students mistakenly interpreting AI feedback as an indication of task completion. Generative AI with voice assistance was perceived as less trustworthy and confidential than human-led interactions, particularly by students with academic difficulties. The analysis also revealed that successful task completion rates were positively correlated with students' satisfaction with the media type, whereas perceptions of trust and confidentiality did not significantly determine satisfaction. Furthermore, satisfaction did not have a significant impact on students' intention to use the media, suggesting that other factors may play a stronger role in shaping their preferences.

This study contributes to understanding the role of media richness and social presence in educational settings, highlighting the strengths and limitations of generative AI with voice assistance for supporting students with academic difficulties. These insights are beneficial for educators and AI developers aiming to improve student engagement and learning outcomes through optimized media channels.

Keywords: Generative AI, Voice assistance, Academic difficulties, Student performance, User experience, Media Richness, Social presence, Perception, Satisfaction, Intention to use.

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Foreward

This thesis was completed as part of the Master of Science in User Experience in a Business Context program at HEC Montréal. It has been reviewed and approved by the Academic Affairs office of the MSc program and the co-directors.

The research project presented in this thesis received approval from the Research Ethics Board (REB) of HEC Montréal under certificate number 2024-5735, confirming its compliance with ethical guidelines for research involving human participants.

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Chapter 1: Introduction

High school dropout rates in North America are becoming a significant social and economic issue (De Witte et al., 2013). In Canada, for example, 10% of individuals aged 20–24 had not completed high school in 2005 (Bowlby, 2005). Similarly, in the United States, 2.1 million young adults aged 16 to 24 had dropped out of high school by 2022, leaving them without a diploma (National Center for Education Statistics, 2024). In the United States, the 2019 dropout rate for students with developmental and educational disabilities was significantly higher compared to their peers without such disabilities, with rates of 10.7% and 4.7%, respectively (National Center for Education Statistics, 2020). Students with disabilities often struggle to read and understand large blocks of information, leading to overwhelm, particularly for those with attention deficits (Woodfine et al., 2008). Meeting the needs of these students is therefore essential in preventing students dropouts (Cardon & Christensen, 1998) and improving educational outcomes(Izzo et al., 2009).

The rapid development and use of generative AI (GenAI) tools (Popenici, 2023), defined as systems capable of creating and designing content that appears original and meaningful, including text, images, derived from existing training data (Feuerriegel et al., 2024), have raised expectations for their potential to support students(Baidoo-anu & Ansah, 2023), particularly those with academic difficulties (Hellesnes et al., 2024). Many of these tools, such as text-based generative AI chatbots, allow students to engage by typing questions and reading responses(aza et al., 2018). Educational organizations such as Alloprof[1] and Khan Academy recognize the importance of such tools and are working to integrate them into their platforms to enhance accessibility and reduce the cost of student support (Moisan, 2024; Kahnmigo, n.d.). The launch of the generative AI chatbot, ChatGPT in November 30, 2022, by OpenAI introduced a powerful AI-driven conversational AI tool capable of engaging in human-like dialogue and performing complex tasks, including writing, explaining intricate topics, and debugging code (Azaria et al.,

[1] Alloprof is a Quebec-based non-profit organization in Canada that provides free educational resources to support students, parents, and teachers. It aims to assist students from elementary to high school by offering tools and services across various subjects, including math, science, French, and history, to make learning more accessible and effective.

2024). It increased accessibility of AI chatbots for users, as it is available 24 hours per day (Panda & Kaur, 2023), allowing users to engage with it at any time according to their needs and preferences. Also, its potential to function as a personalised tutor has raised important questions about its role in supporting students in education (Nguyen et al., 2022).Within educational contexts, generative AI holds promise for various activities, including writing development, enhancing conceptual understanding, generating practice exercises, promoting problem-solving and critical thinking skills, assisting with research, and providing personalised feedback (Ha, 2024). Studying AI is essential to understand its impact on learning, address its limirations, and ensure its effective and ethical integration into education (Sasikala et.al, 2024).

However, text-based communication format can pose challenges for students with learning or language difficulties(Woodfine et al., 2008). These students often struggle to read and understand large blocks of information, leading to overwhelm, particularly for those with attention deficits (Woodfine et al., 2008). Writing difficulties further hinder effective engagement with text-based chatbots (Patty, 2024), limiting their ability to engage and complete tasks(Kumar & Nithiya, 2022). For students with academic and language difficulties, particularly, the speech-to-text capability of such tools could offer a more natural and less intimidating exchange by allowing voice input instead of written commands, enabling a more effective focus on learning (Shadiev et al., 2014). This connection enables students to focus more on understanding the material and solving problems without the strain of spelling, writing and reading extensive text(Kraft, 2023). Heiman and Percel have demonstrated that students with learning difficulties prefer visual or oral explanation to purely texted ones (Heiman & Precel, 2003). Such tools facilitate quicker task completion (Abdo et al., 2023), as students can communicate more naturally by speaking rather than typing (Schmitt et al., 2021). This interaction helps students overcome communication barriers with AI (Padhi et al., 2024), allowing them to achieve more, feel competent, and avoid limitations stemming from challenges in written expression(Bone & Bouck, 2017).

Research shows that students with early language impairments face a significantly higher risk of reading difficulties(Catts et al., 2002). Whereby, children with below-average receptive or expressive language skills are six times more likely to struggle with reading comprehension and word recognition by the second and fourth grades, with nearly 50% developing reading disabilities (Catts et al., 2002). Since reading depends highly on language skills, difficulties in understanding or using spoken language often lead to issues in reading comprehension problems (Hulme and Snowling, 2011). In addition to language impairments, learning disabilities such as dyslexia, dyscalculia, and dysgraphia further hinder academic progress by affecting reading, writing, and information processing (Snowling & Hulme, 2012). For instance, students with dyslexia commonly struggle with spelling and writing fluency, disrupting key stages of writing, such as planning and revising (Hebert et al., 2018). Longitudinal studies also indicate that children whose language impairments persist into primary grades (ages 5 to 6) face heightened risks of future academic challenges, particularly in reading, compared to those whose difficulties resolve earlier (D. V. M. Bishop & Adams, 1990; Stothard et al., 1998). Students with such academic difficulties are consequently at a greater risk of dropping out (National Center for Education Statistics, 2020). These findings underline the need for early intervention that support language development and learning disabilities to improve long-term academic outcomes and prevent dropout.

While generative AI holds promise, its reliance on reading and writing can limit accessibility for some students (Patty, 2024; Kumar &Nithiya, 2022). Integrating text-to-speech (TTS) and speech recognition technologies with AI chatbots may offer a viable solution for students with learning and language difficulties, as these tools enable verbal communication, and reduce the cognitive load of reading and writing, allowing students to focus on learning (Berninger & Amtmann, 2003). For students who struggle with extensive reading and writing, these features ease frustration and provide a smoother, more comfortable learning experience (Bouck et al., 2012).. Research has shown that TTS can make reading more engaging and accessible for students with disabilities; for example, middle school students with disabilities reported greater enjoyment and comprehension when using TTS, as it helped them access grade-level material more fluently and efficiently (Bouck et al., 2012). Students with reading disabilities find TTS beneficial because it helps them read faster, reduces fatigue, and alleviates stress, enabling them to complete tasks more independently and within a manageable timeframe (Elkind et al., 1996). TTS tools can also support students with ADHD by reducing distractibility and stress, helping them maintain focus and experience less fatigue during reading tasks (Hecker et al., 2002). In addition, TTS allows students with reading difficulties to receive spoken feedback (Caverly, 2008.), while speech recognition enables them to ask questions verbally(Mandal et al., 2015), making communication less frustrating (Forgrave, 2002). Auditory input can help students with ADHD maintain focus for longer periods (Bone & Bouck, 2017). Research shows that TTS improves engagement, comprehension, and autonomy by reducing the cognitive demands of word recognition, allowing students to focus on content rather than mechanics (Bouck et al., 2012; Grunér et al., 2018; Moorman et al., 2010). This increased independence and reduced reliance on external assistance enhance students' motivation to continue learning (Edyburn et al., 2005). Addressing these difficulties is essential to bridging the gap between students (Edyburn, 2020), reducing dropout rates (Cardon & Christensen, 1998), and providing the necessary support to help them succeed (Forgrave, 2002).

While generative AI has seen significant advancements (Popenici, 2023), there remains limited understanding of whether generative AI can effectively support students with academic and language challenges(Michel-Villarreal et al., 2023). Traditionally, students rely on teachers, peers, and their schools for learning support (Bojuwoye et al., 2014), raising the question of whether AI chatbots, such as ChatGPT, can replicate the rich, complex knowledge transmission that teachers provide (Rane, 2023). Unlike AI, teachers provide not only academic instruction but also emotional and motivational support (Rane, 2023), encouraging a level of trust and confidentiality that technology may struggle to match (Amoozadeh et al., 2024; Chan & Tsi, 2023; Dzhorobaeva et al., 2024). This highlights the tension between the potential of AI and the established value of human teachers(Chan & Tsi, 2024), especially for students facing significant academic challenges(Hellesnes et al., 2024). Moreover, limited research exits on the effects of generative AI chatbots in education for diverse learner profiles (Wu & Yu, 2024). While some studies emphasize the potential of generative AI in education, such as enhancing learning outcomes and providing personalized support, other research presents conflicting evidence, highlighting concerns regarding its efficiency and potential limitations in educational contexts (Zhang et al., 2024). The specific benefits of speech-enabled AI chatbots for students in education, in comparison to both text-based AI chatbots and digital human tutoring, remain underexplored (Belda-Medina & Kokošková, 2023; Jeon & Lee, 2024; Wang et al., 2024).

The study presented in this thesis aims to address these issues by drawing upon the Media Richness (MRT) and Social Presence (SPT) theories to compare the effectiveness of different modalities in enhancing students' performance. According to MRT, the richness of a communication medium should align with task complexity to minimise ambiguity and miscommunication (Daft and Lengel, 1984). Richer media provide essential features, such as immediate feedback, multiple cues, language variety, and a personal focus, which are crucial for managing complex tasks (Daft and Lengel, 1986). In this study, we assess three media types which closely correspond to MRT: (1) a voice-based chat generative AI, (2) a text-based chat with generative AI, and (3) a text-based chat with teacher. The more the medium aligns with the theory's criteria, the richer it will be considered (Johnson and Keil, 1999). Thus, the voice-enabled generative AI chatbot, with its auditory cues and rapid feedback, represents the richest medium, while the synchronized chat with a human tutor offers personalized feedback but lacks the auditory features. The text-based generative AI chatbot, as the leanest medium, offers adaptability but lacks both auditory and non-verbal cues (Daft and Lengel, 1986; Johnson and Keil, 1999).

The SPT suggests that different communication types convey varying levels of personal, emotional, and engaging connections, impacting users' experiences (Short et al., 1976), is employed to analyse students' perceived risk by examining how different modalities influence their perceptions of trust and confidentiality. According to SPT criteria, the synchronized chat with a human tutor offers the strongest emotional connection among the three modalities (Short et al., 1976), providing real-time communication and personalised responses from a teacher who brings emotional intelligence and empathy, promoting a supportive experience (Al Jaberi et al., 2024). The voice-enabled chat with generative AI follows, as its auditory cues and conversational tone simulate human qualities but lack the depth of empathy found in a human tutor (Short et al., 1976). The text-based generative AI chat has the lowest level of social presence; while it can offer personalised responses, the absence of auditory and visual cues results in a more impersonal experience (Short et al., 1976).

1.2 Research Questions and Research Design

The Iination of MRT and SPT provides a framework to evaluate the effectiveness of each modality in supporting students with academic difficulties. In particular, this framework has a potential in building a theoretical foundation, for assessing student performance and perceptions, which lead to the formulation of the following research questions:

> **Research question 1: To what extent do generative AI chatbots support the academic performance of students compared to teacher-student interactions?**

> **Research question 2: To what extent does generative AI with speech recognition impact the performance, perception, and AI usage intentions of students with academic and language difficulties, compared to text-based AI?**

This study adopts a 2x3 within-subjects experimental design, comparing the performance and perceptions of two groups of students, those with and without academic difficulties, across three distance education modalities: a text-based chat with generative AI, a voice-based chat with generative AI, and a synchronized text-based conversation with a teacher. This resulted in six experimental conditions, with each group interacting with all three modalities: students with academic difficulties (treatment group) using each modality and students without academic difficulties (control group) doing the same. Students were randomly assigned to these modalities while performing grammar exercises in French. Conducted in both controlled and school settings, this study seeks to enhance AI accessibility, bridge educational gaps, and explore the potential of generative AI in education.

1.3 Thesis Outline

This thesis is composed of 7 chapters. The following chapter presents a comprehensive literature review, discussing the Media Richness Model and Social Presence Theory as foundational frameworks for understanding the impact of different media types on student performance, engagement, trust, and confidentiality. This chapter also investigates the specific needs of students with academic and language difficulties, examining how digital tools impact their academic experience. This review situates prior findings within the study's objectives of assessing AI-mediated communication's role in supporting student engagement and shaping perceptions. Then, Chapter 3 reviews previous studies and findings, suggesting how these insights shape the hypotheses of this thesis. Chapter 4 outlines the methodology employed in this study, followed by Chapter 5, which presents the data analysis process and results. Chapter 6 provides a discussion of these findings, and Chapter 7 concludes the thesis by summarizing the main results, discussing contributions to theory and practical implications, and offering recommendations for future research.

1.4 Student Contributions

The student's contribution to this thesis is outlined in Table1. Conducted in the context of user tests at the Tech3Lab, HEC Montréal (Canada), this table summarises the key steps involved in completing the thesis, detailing tasks performed by the student and contributions from other parties, such as the co-directors and the lab's operations team. The student's involvement is quantified as percentages for each step, reflecting their input throughout the process, though these percentages do not account for the guidance and support provided by the co-directors.

Table 1. Student Contribution Table

Research Process	Student Contribution
Research question	**Problem Definition (80%):** Identified the research gap to shape the problem and its implications. The industrial partner defined the problem, which the student contextualised within academic research.
Literature Review	**Literature Review (100%):** Conducted research to identify relevant articles, reviewed them for relevance, and excluded those that did not align with the research topic.
Conception and Experimental design	**Ethics Approval (80%):** Submitted the application to the HEC Montreal Research Ethics Board, providing the required documentation. The application and documents were reviewed by the lab's operations team and supervisors. **Experimental Protocol and Stimuli Development (80%):** Developed and structured the experimental protocol, tested, and integrated generative AI prompts, and designed the Qualtrics questionnaire.
Recruitment of participants	**Laboratory setting students (90%):** Developed inclusion/exclusion criteria and identified participants through connections, schools, and social media platforms. **School setting students (10%):** Established criteria and coordinated with operations teams to ensure the school had the necessary recruitment information.
Pre-tests and data collection	**Setup and data collection (80%)**: Installed the multi-device setup and conducted multiple tests and iterations to refine both the setup and the data collection process. During testing, I moderated sessions and observed participants, with technical support and organizational assistance provided by the Tech3Lab operations team.
Data Analysis	**Data Extraction and Analysis (80%):** Extracted the data and entered it into Tobbi and Observer XT, with analysis support provided by the Tech3lab. Independently interpreted and presented results based on the analysis.
Writing the Thesis	**Thesis Writing (100%):** All chapters were written by the student, incorporating feedback and advice from co-authors and supervisors.

Note. The percentages reflect the student's independent work and do not include the guidance and input provided by the project supervisors.

Chapter 2: Literature review

This chapter explores the theoretical and empirical foundations that inform our understanding of how different types of media influence the effectiveness of communication and learning. We begin by examining the concept of media richness and its role in determining the appropriateness of different media for transmitting information in an educational context. According to Media Richness Theory, richer media are more effective in resolving equivocality because they enable a more immediate, nuanced, and engaging exchange of information (Daft & Lengel, 1986).

We then investigate into the concept of social presence, which reflects the extent to which a medium allows individuals to perceive a sense of personal connection and emotional engagement (Short et al., 1976). Research indicates that media with higher social presence cultivates an environment that stimulate interpersonal collaboration (Srivastava and Chandra, 2018). Previous findings also suggest high social presence in education is also associated with increased student engagement (Ngoyi et al., 2014), enhanced perceptions of learning, and greater overall satisfaction (Lowenthal, 2018).

Lastly, this chapter introduces the three types of media analyzed in this study with different levels of media richness and social presence: text-based chat with generative AI, voice-based chat with generative AI, and a text-based chat with a teacher. We examine their respective characteristics in terms of media richness and social presence and discuss how these modalities affect students' learning performance, perceptions, satisfaction, and their intention to use them. The discussion emphasizes how different media can shape these outcomes by either enhancing or limiting students' ability to process information effectively and feel supported. By synthesizing existing research, this chapter not only provides a theoretical framework for understanding how media types influence learning and perception but also prepares the groundwork for the next chapter, where we assess the hypotheses and the methodology driving our experimental study.

2.1 Understanding Media Types in Communication and Distance Learning

Effective communication is central to education (Morreale et al., 2009), as students learn through both explicit and implicit exchanges with teachers and peers (Ellis, 2009). Recently, education has increasingly embraced digital communication channels (Manea, 2020), reflecting a shift toward online learning and a reduced dependence on traditional face-to-face interactions (Hislop, 2009).

Distance education is characterised by a continuous separation of teacher and learner, guided by an educational organisation that oversees course planning, learning materials, and student support (Keegan, 1996). It relies on technical media such as print, audio, video, or the internet to provide content and facilitate two-way communication (Keegan, 1996). Learning often occurs individually rather than in groups, with limited opportunities for in-person or virtual meetings to support both instruction and social exchanges (Keegan, 1996).

Online learning has seen significant growth over recent years as institutions increasingly embrace online education options (Hajhashemi et al., 2017). A survey by the National Center for Educational Statistics (NCES) found that, during the 2000–2001 academic year, 56% of degree-granting colleges and universities provided distance learning courses (Waits, 2003). By 2003, 34% of a representative sample of 1,000 higher education institutions offered fully online degree programs (I. E. Allen & Seaman, 2004).

Distance learning provides several advantages, including flexibility and self-paced study, allowing students to choose when and where they learn according to their personal schedules (Fidalgo et al., 2020). This approach enables students to select their preferred learning methods, such as watching videos or reading materials online, without the need for commuting, making it both time-efficient and cost-effective (Means et al., 2009). The abundance of free or low-cost resources online, such as educational videos, articles, and learning platforms, reduces expenses, as does the decreasing cost of internet access and devices (Means et al., 2009). Students also have unlimited access to a vast range of information on the internet (Dahalan et al., 2012).

However, distance learning has its limitations. For instance, It restricts human interaction, as students primarily engage with digital interfaces, and while some platforms offer discussion forums, they lack the depth of face-to-face communication (Weidlich et al., 2024). Furthermore, other disadvantages include challenges in maintaining student motivation, delays in receiving immediate feedback, the necessity of consistent and dependable access to technology, and occasional issues with accreditation (Fidalgo et al., 2020). Distance learning is also often theoretical, limiting its applicability in hands-on fields, such as scientific specializations, where practical experience is essential (Hosseindoost et al., 2022).

Another significant challenge in distance learning is retaining students, as studies show that online learners are more likely to discontinue their studies compared to those in traditional classrooms. For instance, Research found that 70% of adult learners enrolled in corporate online programs failed to complete them (Meister, 2002). Similarly, the Corporate University Xchange (2000) highlighted learner retention as a major challenge in online education. Research has consistently shown that dropout rates are higher among online students than those in traditional face-to-face classes (Hiltz, 2019; Phipps & Merisotis, 1999).

In the evolving educational environment, the choice of media plays an important role in how effectively information and emotions are conveyed, a concept known as media richness (Daft & Lengel, 1986). According to MRT, diverse communication methods (in-person, live digital platforms, and asynchronous tools) are employed, understanding their effectiveness in transmitting information becomes essential (Daft & Lengel, 1986). MRT provides a framework for explaining how various media differ in their ability to reduce ambiguity and enhance understanding (Daft & Lengel, 1986).

Media Richness Theory explains that communication channels vary in their ability to transmit information effectively and reduce ambiguity or misunderstandings (Daft & Lengel, 1986). The theory distinguishes between two types of information conveyed through media: explicit information, which refers to the factual content of a message, and symbolic information, which includes implicit components such as emotional tone, non-verbal cues, and the sender’s intent (Daft & Lengel, 1986). Daft and Lengel (1986) developed a hierarchy of media richness based on four key criteria: the immediacy of feedback, the medium’s ability to convey multiple cues, the use of natural language, and the level of personal focus. According to these criteria, face-to-face communication ranks as the richest medium. The hierarchy then follows, in decreasing order of richness, with video, telephone, email, postal letters, notes, memos, flyers, and bulletins.

Media Richness Theory (MRT) explains how different communication channels vary in their ability to convey information effectively, particularly in managing ambiguity and enhancing message clarity. Richer media, such as face-to-face exchanges and live conversations, are better suited for ambiguous or uncertain contexts because they provide immediate feedback, incorporate multiple cues like tone and gestures, use nuanced language, and promote a personal focus, making communication more engaging and tailored (Daft & Lengel, 1986). In contrast, leaner media, such as emails (Bergin et al., 2016), are more appropriate for straightforward tasks in stable environments, as they lack these features and carry minimal risk of misinterpretation (Daft & Lengel, 1986).

By reducing equivocality, the uncertainty when messages can be interpreted in multiple ways, richer media minimize misunderstandings and promote shared understanding (Daft & Lengel, 1986). MRT thus offers an important framework for analyzing how media richness impacts communication effectiveness, particularly in complex or emotionally nuanced interactions (Daft & Lengel, 1986).

However, applying MRT to educational settings reveals a nuanced picture. Research in distance education has shown that richer media, such as video and interactive platforms, are associated with higher student satisfaction, enhanced communication between faculty and students, and greater appreciation for the course delivery format (Shepherd & Martz Jr., 2006). Yet, a meta-analysis of studies using MRT in computer-assisted instruction indicates that leaner media can sometimes lead to better learning outcomes, with audio leading to higher achievement scores than video, and plain text outperforming text combined with graphics (Timmerman & Kruepke, 2006). Also, studies examining satisfaction separately from achievement have found that while richer media such as video and audio are closely linked to learner satisfaction, leaner media, such as text, tend to be associated with higher achievement scores (Otondo et al., 2008).

This suggests a potential discrepancy in MRT's application within educational contexts, indicating that while richer media may enhance satisfaction (Shepherd & Martz Jr., 2006), leaner media might better support focused learning outcomes graphics (Timmerman & Kruepke, 2006). This nuanced relationship highlights the need for further research to refine MRT's use in education, exploring how different media types align with diverse educational goals.

2.2 The Role of Social Presence in Distance Learning Interactions

Social presence has been defined as "the extent to which one feels the presence of a person with whom one is interacting" (Latchman & Latchman, 2000) and "the feeling one has that the other persons are involved in a communication exchange" (Carnevale, 2000). In essence, it reflects the degree to which individuals feel that the person they are communicating with is "real" and emotionally present. A high level of social presence develops a sense of connection and awareness of the other person's emotions and intent (Short et al., 1976).

Social Presence Theory is linked to two key concepts: Intimacy and Immediacy (Short et al., 1976). Intimacy refers to the closeness experienced in an interaction and is affected by factors such as physical proximity, eye contact, non-verbal cues such as smiling, and engagement in personal conversation topics (Argyle & Dean, 1965). Immediacy refers to the psychological distance a communicator forms through their behaviour (Wiener & Mehrabian, 1968). It is expressed through non-verbal cues (e.g., physical proximity, facial expressions, or clothing) and verbal cues (such as tone and voice).

Face-to-face communication offers the highest level of social presence because it incorporates non-verbal cues such as gestures, vocal tone, and facial expressions, helping students interpret emotions and feel a stronger personal connection. In contrast, text-based communication (e.g., emails or forum posts) provides low social presence, as it lacks verbal and non-verbal cues and delays feedback, making it more difficult to establish emotional connections (Short et al., 1976). Faster feedback enhances the perception of social presence, while delays reduce it, making exchanges feel less personal (Miranda & Saunders, 2003; Sproull & Kiesler, 1986). For instance, paper-based and text-based communication, such as email, are considered low in social presence due to the absence of verbal and emotional cues (Miranda & Saunders, 2003). Furthermore, computer-mediated communication can weaken social presence, as these interchanges tend to be self-absorbed, with less consideration for others' emotions and needs (Sproull & Kiesler, 1986). However, instant messaging, which provides real-time exchanges with immediate feedback, has been found to promote deeper connections than asynchronous forms such as email (Winter & Kuyath, 2006). Research shows that the shorter the delay in response, the higher the perceived social presence (Miranda & Saunders, 2003; Sproull & Kiesler, 1986).

Previous studies in distance learning have shown that students' perceptions of their instructor's social presence can significantly influence their satisfaction and learning outcomes. For example, one study found a strong association between the perceived presence of the instructor and both affective learning and student satisfaction (Russo & Benson, 2005). Another study indicated that students with heightened perceptions of social presence reported greater levels of perceived learning and satisfaction with the instructor, with social presence perceptions serving as significant predictors of their entire learning experience (Richardson, 2001).

Both Social Presence Theory and Media Richness Theory emphasize the importance of selecting the appropriate communication medium to match the context and task at hand, ensuring effective outcomes and minimizing miscommunication (Daft and Lengel, 1986 and Short et al, 1976). In education, face-to-face communication has long been the standard for teaching (O'Flaherty & Laws, 2014) and has proven effective in enhancing student learning (Lepper et al., 1990) and engagement (Cooper, 2023). However, with recent technological innovations (OpenAI, n.d.), it is important to inspect whether generative AI chatbots can similarly support students, improve their academic performance, and provide positive learning experiences. This study aims to investigate how students perceive these AI tools compared to their exchanges with a teacher, assessing both their effectiveness in meeting students' needs and the students' general satisfaction with each medium.

2.3 Generative AI vs. Human Teachers: The Impact on Learning and Engagement

2.3.1 Generative AI chatbot

As UNESCO (2019) noted, artificial intelligence (AI) holds transformative potential in education, with applications becoming increasingly widespread. Also, in recent years, the integration of artificial intelligence (AI) into education has attracted considerable attention, with an increasing number of educational institutions and organisations investigating the potential advantages of technologies using AI (Dwivedi et al., 2021; Su & Yang, 2022). This potential was further realised with the release of the generative AI tool, ChatGPT on November 30, 2022, expanding AI's accessibility (Baidoo-anu & Ansah, 2023). ChatGPT, a language model initially based on GPT-3, predicts word sequences to generate human-like communication (Baidoo-anu & Ansah, 2023). The latest version, GPT-4, offers enhanced capabilities, including real-time internet access, making it more powerful (OpenAI, n.d.).

Generative AI chatbots such as ChatGPT are designed to engage in conversational exchanges while providing timely, personalised feedback (OpenAI, n.d.). This makes it capable of answering students' questions, as well as clarifying and explaining their study material (Baidoo-anu & Ansah, 2023). ChatGPT uses Reinforcement Learning with Human Feedback, which gives it the ability to immediately answer the questions as well as reduces the likelihood of generating inaccurate or harmful content (Xu & Ouyang, 2022). It is also able to offer students immediate assistance whenever they want, this eliminates their need for their teachers to answer when studying, as it is available anytime (Rahman & Watanobe, 2023). This corresponds with the immediacy of feedback criteria of the MRT (Daft and Lengel, 1986), as well as SPT's immediacy criteria (Short et al., 1976)

Generative AI models such as ChatGPT offer personalized tutoring by identifying student misconceptions and providing tailored feedback, enhancing individual learning experiences (Chen et al., 2020). Generative AI tool's language translation capabilities (Johnson et al., 2016) also have the potential to improve accessibility, particularly for bilingual students or those studying in non-native languages, enabling a better understanding of educational materials (Nikolopoulou, 2024).

Furthermore, research highlights generative AI's potential to enhance learning through personalized tutoring, adaptive learning, and interactive engagement. For instance, Students can ask questions, receive customized feedback, and access tools such as language translation, study strategies, and revision advice (Baidoo-anu & Ansah, 2023).The ability to refine the tool's output through prompt engineering adds another layer of customization, allowing students to tailor the conversations to their needs (Nazari & Saadi, 2024).

This adaptability resonates with the personal focus and language variety dimensions of media richness (Daft and Lengel, 1986), demonstrating ChatGPT's ability to support diverse student requirements effectively through tailored feedback and tutoring. When comparing to human tutor, a study demonstrated that the tool could be able to provide more detailed feedback and better summarise student performance than human instructors, with assessments corresponding with those of teachers (Y. Wu et al., 2016). Given limited school resources (Greenwald, R et al., 1996), automated feedback systems such as ChatGPT have the potential to support learning by offering personalised feedback, which is crucial for improving learning and achievement (T. Ryan et al., 2023). Research demonstrates AI's educational potential, with AI-powered adaptive learning platforms improving student performance, engagement, and motivation (Luo & Hsiao-Chin, 2023). Furthermore, it demonstrated that generative AI tools, such as ChatGPT , have the potential to significantly improve programming students' performance by modifying the difficulty of problems to suit their knowledge level (Baidoo-anu & Ansah, 2023).

As students increasingly rely on the internet to gather information and to explore new subjects(Bhagat et al., 2016; Çetiner et al., 2012), a diversity of digital platforms has emerged to offer academic support (Alloprof, nd; Khan Academy, nd). Recognizing this shift, educational organizations are leveraging the potential of generative AI to revolutionize education by not only assisting students in their learning but also supporting teachers in planning and providing educational material (Alloprof, nd; Khan Academy, nd). For instance, Khanmigo, a GenAI-based educational app from Khan Academy, is a subscription-based tool powered by GPT4 through an API (Shetye, 2024).. It is designed to support learning activities and is particularly well-suited for educational contexts as a specialized AI teaching assistant, thanks to its teacher-curated content, which minimises false or biased information (Shetye, 2024). Unlike other AI tools, it does not provide answers directly to students; instead, it patiently guides them through problems, enhancing deeper understanding and independent learning (Shetye, 2024). Integrated into Khan Academy's extensive content library, Khanmigo covers subjects such as math, humanities, coding, and sciences. Unlike other AI tools, it guides learners to find answers rather than providing them directly, mimicking a teacher’s approach (Shetye, 2024).

Khanmigo includes various activity formats tailored to diverse learning needs(Shetye, 2024). The "Tutor Me" feature helps learners solve problems in subjects such as math, science, and humanities by breaking tasks into manageable steps and offering additional practice when necessary(Shetye, 2024). The "Refresh" feature allows students to test their understanding through quizzes that adapt to their grade level and prior responses, providing feedback and generating new questions based on their demonstrated knowledge (Shetye, 2024). The "Write" feature supports learners in essay writing, story crafting, and brainstorming, particularly focusing on admission essays by offering constructive feedback. For younger learners, the "Debate" feature encourages critical thinking and topic brainstorming, catering to elementary, middle, and high school students (Shetye, 2024). The "Chat" feature enables learners to have simulated conversations with literary characters or historical figures, making learning engaging and interactive. Also, the "Play" feature offers word-based games that encourage creativity and exploration. Khanmigo also includes an "Extra" section, which provides opportunities for learners to engage with the AI on topics that spark their curiosity, promoting exploration and deeper engagement (Shetye, 2024).

Alloprof is also developing an AI virtual assistant called AlloFlo, to support primary and secondary school students by providing personalized and instant help (Moisan, 2024). The aim is to ensure students feel supported, even when their teachers or peers are unavailable (Moisan, 2024). This assistant is designed to guide students through their learning process, helping them understand and solve academic challenges while addressing their specific needs (Moisan, 2024). On AlloFlo, students will be able to engage with a conversational chatbot to ask questions on any subject (Moisan, 2024). The chatbot will utilize Alloprof's vast pedagogical resources to deliver fast, accurate, and educationally sound responses. Alloprof believes that this initiative can be part of the solution to Quebec's teacher shortage by providing every student with their own personal tutor (Moisan, 2024). The new chatbot is expected to launch in June 2025 (Moisan, 2024).

However, generative AI chatbots, while innovative and adaptable, have been critiqued for various limitations that affect their effectiveness and ethical use in education (Lo, 2023). A literature review conducted by Lo (2023), highlights several challenges associated with the use of generative AI in education, particularly concerning its accuracy, reliability, and implications for academic integrity. Its reliance on large datasets can lead to inaccuracies and biases, as it may be trained on research predominantly conducted in high-income countries or textbooks with limited global applicability (Mbakwe et al., 2023; Sallam, n.d.). Furthermore, studies have found that the generative AI tool often generates incorrect or even fabricated information known as “hallucinations", which can be misleading for students relying on it for learning (Mogali, 2024). Its limitations have been observed across domains such as programming (Megahed et al., 2024), where it produces incorrect code and fails to resolve errors, as well as in mathematics (Frieder et al., n.d.) sports science and psychology (Szabo, 2023), and health professions (Fijačko et al., 2023).

Concerns about academic integrity have also emerged, as content generated by generative AI often bypasses plagiarism detection tools such as Turnitin and iThenticate (Khalil & Er, 2023; Ventayen, 2023). For instance, a study found that essays produced by ChatGPT had low similarity scores, averaging 13.72% on Turnitin and 8.76% on iThenticate, classifying them as highly original despite being AI-generated (Khalil & Er, 2023). Students who used ChatGPT were more likely to engage in plagiarism compared to those who did not, thereby compromising academic integrity (Bašić et al., 2023). Apart from issues of plagiarism, generative AI tools also raise significant concerns about fairness, as some students have access to its advanced capabilities to generate high-quality content, giving them an advantage over peers who lack similar access or resources (Cotton et al., 2024). This imbalance develops disparities in academic opportunities (I. Khan & Paliwal, 2023) and makes it challenging for instructors to fairly evaluate student performance (Farazouli et al., 2024).

The use of generative AI in education presents both opportunities and challenges (Baidoo-anu & Ansah, 2023), requiring a careful balance between its potential benefits and inherent risks. Generative AI poses significant risks, such as producing incorrect information, bypassing plagiarism detection, and weakening cognitive autonomy (Cooper, 2023; Lo, 2023; Rani et al., 2023). Therefore, effective integration of AI in education necessitates careful planning, digital literacy, and ethical awareness (Krügel et al., 2022), along with well-defined strategies for incorporating AI tools into curricula (Rudolph et al., 2023; Tan, 2022).

Despite these challenges and based on the findings we discussed in this chapter, it appears that generative AI demonstrates potential to enhance educational experiences by providing timely, tailored feedback and human-like responses (Baidoo-anu & Ansah, 2023). Its ability to adapt explanations based on student needs through prompt engineering (Nazari & Saadi, 2024) corresponds with the personal focus criterion of media richness, and its flexible language capabilities meet the language variety criterion (Daft and Lengel , 1986). However, the absence of voice assistance and non-verbal cues, such as tone of voice, body language, and facial expressions, limits the richness and social presence of the generative AI tool based on the criteria of MRT (Daft and Lengel, 1986). Based on these factors, it can be argued that ChatGPT is rich in immediacy, language variety, and personal focus, but leaner in multiple cues due to the lack of verbal and physical aspects (Daft and Lengel, 1986).

In particular, the impact of generative AI tools is not uniform across all student profiles (Johnson & Johnson, 2020). Different groups of students, based on their academic performance and learning needs, may experience varying levels of benefit from these tools. Research suggests that high-achieving students benefit more from these platforms than their lower-performing peers, highlighting the need for additional support to guarantee equitable benefits (Johnson & Johnson, 2020).

One potential solution to overcome these limitations is the integration of voice-based interfaces. While text-based generative AI provides personalised support, its lack of auditory and non-verbal cues reduces media richness and social presence (Daft and Lengel, 1986; Short et al.,1976). Voice-based interfaces have the potential to enhance the naturalness of interactions by incorporating auditory feedback (Schmitt et al., 2021), creating more effortless and natural conversations (Schmitt et al., 2021) which increases the richness of the generative AI communication modality (Daft and Lengel, 1986). Using audio feedback develop greater social presence (Portolese & Trumpy,2014) which could increase student engagement (Imlawi, 2021), potentially bridging gaps for students with diverse learning needs, as it has been shown to positively impact learning performance(Schindler et al., 2017). The following section inspects how voice-enabled generative AI could further enhance educational experiences by tackling these challenges and limitations.

2.3.2 Voice assistance

Personal assistants such as Siri, Alexa, Cortana, and Google Assistant are speech-based Natural User Interfaces commonly integrated into smartphones and smart speakers (López et al., 2018). These assistants operate by receiving voice commands and performing tasks such as setting alarms, reading news, playing music, making calls, setting reminders, and answering questions (Hoy, 2018). Through speech recognition, they convert spoken language into text or commands, enabling natural voice communication(v et al., 2021).

Voice assistants rely on technologies such as voice recognition, speech synthesis, and Natural Language Processing (NLP) to offer their services. Most of their processing occurs in the cloud, where voice commands are converted to text, processed, and returned as spoken responses(Terzopoulos & Satratzemi, 2020). NLP allows the assistants to interpret human language, while machine learning helps them recognize patterns and adapt to user preferences over time (Sheppard, 2017).

The use of voice assistants in the US is steadily increasing, with projections indicating that by 2028, 48.6% of the population, 53.4% of internet users or 170.3 million people, will use these technologies (e-Marketer, 2024). Studies highlight the positive impact of this technology. For instance, a study found that the convenience, ease of use, and hands-free operation of voice assistants are key factors driving user satisfaction, with participants expressing enjoyment and curiosity in their experience with the technology (Rzepka, 2019).

Voice assistants are also beneficial for individuals with disabilities. For example, speech input has proven useful across various applications for users with motor impairments, such as enabling text entry on desktops (Manaris et al., 2002; Wagner et al., 2012) and smartphones (Naftali & Findlater, 2014), wheelchair control (Pacnik et al., 2005; Simpson & Levine, 2002) , and facilitating "free-hand" drawing (Harada et al., 2009). For individuals with visual impairments, speech input is more widely utilized on mobile devices compared to sighted users , as it offers greater efficiency for tasks such as text entry (Azenkot & Lee, 2013) and web browsing (Ashok et al., 2014). A study on using voice-based smart home control discovered that both older adults and individuals with visual impairments expressed positivity toward using voice commands to manage smart home systems (Portet et al., 2013). Other studies also revealed that users with multiple sclerosis (Stahl & Laub, 2017) and older adults (Callejas & López-Cózar, 2009), many of whom experienced motor impairments, expressed a preference for voice-based control of home features (e.g., doors, windows). The older adult group also showed a strong interest in using voice for communication, such as via phone (Callejas & López-Cózar, 2009).

In education, previous findings emphasised the potential of speech-to-text technologies to reduce barriers for students with impairments such as dyslexia, promoting more inclusive learning environments (Kasneci et al., 2023). Another study found that using audio feedback in a distance learning environment led students to perceive their instructor as more caring about their learning (Ice et al. ,2007). The study suggests that audio feedback may enhance students' perception of the instructor's social presence, making students feel more connected to the instructor as a person rather than a distant figure providing feedback (Ice et al. ,2007). This use of audio feedback helped students experience a stronger sense of social presence and engagement from their instructor (Portolese & Trumpy, 2014).

While voice assistance offers numerous benefits, it also poses significant challenges. Privacy is a major concern, as individuals are more cautious about sharing private information than non-private information with voice assistants (Easwara Moorthy & Vu, 2015). Smart home technologies amplify these concerns through pairing and discovery protocols that reveal device information (Wu, D et al., 2016), insecure communication channels leaking sensitive data (Cui & Stolfo, n.d.), device vulnerabilities enabling attackers to spy on residents or disrupt their lives (Denning et al., 2013), and affordability (Brush et al., 2011). Individuals with disabilities, in particular, may be more willing to share and record smart home data compared to those without disabilities (Beach et al., 2009).

Despite these drawbacks, we believe that incorporating voice assistance into generative AI chatbot has the potential to benefit students. By adding a voice-user interface to generative AI tools, students can communicate through voice rather than text, thereby increasing the multiple cues criterion of media richness (Daft and Leger, 1986). This enhancement makes ChatGPT with voice assistance a richer medium compared to the text-based version, as it incorporates both auditory cues and immediate feedback, improving the universal richness of the interaction. It also enhances students' sense of the social presence of the generative AI chatbot by enabling more natural conversations and providing auditory feedback through voice responses (Portolese & Trumpy, 2014).

While voice-based generative AI offers enhanced media richness by incorporating auditory cues and promoting more natural exchanges, it still cannot fully replicate the depth of emotional connection and nuanced support provided by human tutors (Jeon & Lee, 2024). While AI chatbots provide immediate responses and personalized feedback, human tutors offer empathy, adaptability, and emotional support that AI struggles to replicate (Jeon & Lee, 2024). This limitation affects the chatbot's ability to match the social presence of human tutors, as defined by the social presence criteria (Short et al., 1976). The following section examines the role of human tutors in providing personalised guidance, personalized feedback, and emotional support, highlighting how their ability to engage students through nuanced communication and contextual cues maintains the highest level of media richness and social presence. However, challenges such as cost, burnout, and limited availability also influence the accessibility and effectiveness of human tutoring (Bloom. 1984), which raises important considerations for its role alongside AI tools.

2.3.3 Text-based human tutor

Human tutors play a vital role in enhancing student learning by offering personalised guidance and feedback. Research demonstrates that tutors effectively direct students to appropriate resources, provide precise hints to prevent confusion, and promote independent problem-solving (Lepper et al., 1990,1993).Their ability to offer interactive feedback develops both improved learning and increased motivation (Lepper et al., 1993), while tailoring teaching methods to individual needs, showing richness in personal focus (Corno, 2008). However, one-on-one tutoring can be costly and may lead to teacher burnout, reducing its accessibility (Bloom, 1984). Some tutors may also lack the specialised training required to support students with disabilities (Nguyen et al., 2022). This suggest that according to MRT criteria (Daft and Lengel, 1986), while tutors demonstrate richness in language variety through their ability to adapt their communication styles (Parsons et al., 2017) the immediacy of feedback is leaner due to their limited availability (Wiggan et al., 2021). Moreover, emotional support from teachers is a vital component of high-quality instruction (Studer, 2004; Wubbels & Brekelmans, 2005; Pianta & Hamre, 2009) with research showing that teacher-provided emotional support positively affects students' motivation and engagement (Cooper, 2014; Patrick et al., 2007; Reyes et al., 2012; Roorda et al., 2011; Ryan & Patrick, 2001; Skinner et al., 2008).These factors suggest that human tutors can express emotions and offer guidance to prevent frustration, showcasing richness in multiple cues through emotional support and verbal reinforcement (Short et al., 1976).

During synchronous text-based conversations with a tutor, students receive feedback with clarifications that minimise misunderstandings (Alloprof, n.d.). The teacher can employ nuanced language tailored to the student's specific needs (Stahl & Laub, 2017) and academic level(M. H. Allen et al., 2013). Furthermore, the teacher can convey contextual cues through spelling, grammatical markers, emoticons as well as the tonality of the voice (Riordan et al., 2010) helping students interpret intent more accurately and reduce ambiguity (Braumann et al.,2010; Harris and Paradice, 2007). By using a digital cue in writing, the teacher creates a comfortable learning environment (Rubel & Wallace, 2010), enhancing the student's experience and reinforcing the social presence of the exchange (Short et al., 1976; Dixson et al., 2017). Building on the factors outlined earlier, the teacher's reliance on text-based communication without voice interaction is associated with the highest level of social presence (Short et al.,1976) and an intermediate level of media richness (Daft and Lengel, 1986) among the three modalities examined in this study.

2.4 The Influence of Media Richness on Student Performance

Learning performance refers to the extent students acquire and apply knowledge (Wu and Yu, 2024). Research highlights that academic and social engagement as key psychological factors influencing students' academic performance (Sá, 2023). While Astin (1999) defines involvement "the amount of physical and psychological energy" a student invests in their education, this concept closely aligns with the definition of academic engagement used in this study.

In this thesis, learning performance is measured through three indicators: successful task completion rate, which refers to the completion of a task without significant errors or deviations from the correct steps, resulting in the desired outcome (Law Insider, n.d.) ; task completion time, defined as the total duration measured in seconds, required to complete a single task (Rummel, 2014) , and behavioural engagement, which refers to the number of prompt sent by the student when using the three types of media.

A study demonstrated that richer media in distance education, such as video and voice modalities, could be more effective and enhances student satisfaction compared to leaner media such as text (Shepherd & Martz Jr., 2006). Effectiveness in this study was measured by student perceptions of how well the medium transmitted the course content (Shepherd & Martz Jr., 2006).

In a related context, research with graduate students showed that generative AI significantly enhanced students' academic performance, suggesting that these tools can effectively support learning (Chan & Tsi, 2023). In addition, TTS systems have been found to reduce cognitive load by decreasing working memory demands (Nordström et al., 2019; Hebert et al., 2018) and promoting higher engagement and comprehension (Grunér et al., 2018).

Similarly, human tutoring, which is often perceived as the richest medium in face-to-face contexts (Daft and Lengel, 1986), has consistently been shown to improve student learning (Lepper et al., 1990). Further findings emphasized that positive student-teacher relationships increase behavioral and emotional engagement, leading to improved academic outcomes (Cain et al., 2003).

Integrating artificial intelligence in educational settings has been shown to enhance student engagement by offering engaging, personalised, and immersive learning environments(Chen et al., 2020; Malik et al., 2019). Incorporating voice modality further reduces task completion time by providing a faster (Abdo et al., 2023), more fluid user experience (Schmitt et al., 2021), thereby decreasing effort (de Melo et al., 2020) and having the potential to improve students' academic performance (Devkota et al., 2024). A study in the UAE found that users felt more satisfied with voice communication than typing, as it enabled faster task completion and feedback (Abdo et al., 2023). Moreover, voice assistants have been shown to lower cognitive load, allowing learners to focus more effectively, and perform better compared to those who did not use the tool (Brachten et al., 2020). Research also suggests that positive affective relationships with teachers lead to greater student engagement and improved academic outcomes (Li et al., 2022).

2.5 Social Presence and Student Perceptions of Trust and Confidentiality

High social presence develops emotional connection (Short et al., 1976), building students' trust (Ogonowski et al., 2014) and enhances the perception that their personal information are protected (Champness, 1972). However, trust and confidentiality are distinct concepts. Trust is the belief that the recommendations and responses provided by AI or human agents are dependable and credible. (Shin, 2021). In contrast, confidentiality focuses on privacy and data security, defined as the "agreement with persons about what may be done with their data" (Sieber, 1992).

A study found that adolescents generally reveal high levels of trust in their teachers (Lee, 2007) . In contrast, a comparative study of undergraduate and graduate students in India and the USA revealed neutral attitudes toward generative AI, with students neither strongly trusting nor distrusting these systems (Amoozadeh et al., 2024). Building trust and rapport through personal exchanges is crucial for teachers in promoting a positive learning environment, a process that AI systems struggle to replicate (Chan & Hu, 2023). Further findings further emphasised that AI systems lack the emotional intelligence and accountability necessary to be fully trusted (Ryan,2020).

Confidentiality concerns are more prominent with AI systems, which raise worries about data security and privacy (Chan & Hu, 2023; Chung et al., 2017). In a study conducted in six Hong Kong universities involving 399 students, more than half of the students' expressed concerns about the accuracy and transparency of information provided by generative AI tools such as ChatGPT. These students feared that their personal data might be collected based on the prompts they submitted (Chan & Hu, 2023). Recent incidents have also raised public awareness about privacy and data security issues related to virtual assistants (Chung et al., 2017). For example, vulnerabilities in Amazon Alexa's system were identified by Check Point, which highlighted potential risks of data breaches, leaving users concerned about privacy and control over their personal data.(*Turning Alexa Bad*, 2020)

2.6 Supporting Students with Academic and Language Difficulties: The Need for Tailored Media Approaches

2.6.1 Understanding their difficulties.

Not all students demonstrate the same learning performance (Felder & Brent, 2005) or hold similar perceptions of various media types (Dospinescu & Dospinescu, 2020). Factors such as academic challenges and language difficulties influence how students engage with and benefit from different communication channels (Johnson & Johnson, 2020), shaping both their outcomes and experiences (Amerstorfer & Freiin von Münster-Kistner, 2021). Moreover, research has found that reading difficulties and persistent academic challenges are associated with school disengagement, particularly among at-risk groups (Williams et al., 2023). However, the increase of school engagement can significantly improve their completion rates (Williams et al., 2023).Understanding these differences is essential for developing personalised interventions that can more effectively support students' needs (Felder & Brent, 2005).

Students with learning difficulties face persistent challenges that extent beyond high school, contributing to higher unemployment rates, lower income, and poorer health outcomes (Snyder & Dillow, 2013). The dropout rate for students with developmental and educational disabilities is 10.7%, compared to 4.7% for their peers without disabilities in 2019 (National Center for Education Statistics, 2020). In postsecondary education, they are less likely to enrol, more likely to drop out, and less likely to achieve career success (Burgstahler, n.d.).

These difficulties typically originate from issues with text comprehension, word decoding, and reading fluency (Cortiella & Horowitz, 2014; Fletcher et al., 2012). For example, reading disabilities impair students' ability to recognize words and understand longer passages, leading to poor comprehension (LaBerge & Samuels, 1974). Since decoding is fundamental for advanced language comprehension, students must first master these basic skills to succeed (Cain et al., 2004).

Some of their challenges can also stem from both internal factors, such as behavioural or emotional issues (e.g., impulsiveness, hyperactivity), and external factors such as family instability, poverty, and social challenges (Tyler & Lofstrom, 2009). Learning disabilities, including dyslexia, dyscalculia, and dysgraphia, further hinder academic progress by affecting reading, writing, and information processing (Snowling & Hulme, 2012; Rice, 2004). For example, students with dyslexia struggle with spelling and writing fluency, disrupting critical stages of writing such as planning and revising (Hebert et al., 2018). Poor study habits, time management issues, socioeconomic status, individual characteristics, family factors as well as educational contexts intensifies the challenges with their academic performance (Suleiman et al., 2024).

Students also face language difficulties that stem from interconnected factors (Catts et al., 2002). One key factor is phonological processing deficits, which impair their ability to recognize and manipulate sounds, making it challenging to decode words and build reading fluency. Poor phonological awareness, such as difficulty identifying rhymes or breaking words into syllables, further disrupts the ability to connect sounds with corresponding letters (Catts et al., 2002). In addition, limited rapid naming ability affects fluency, as students struggle to retrieve words efficiently while reading (Catts et al., 2002). Articulation impairments complicate early literacy development by interfering with accurate pronunciation, which can create obstacles in acquiring foundational language skills (Catts et al., 2002). Moreover, receptive language difficulties, the ability to understand spoken or written language, hinder students' comprehension, and ability to follow instructions. Finally, expressive language challenges impair their ability to form coherent sentences and communicate ideas effectively, creating barriers in both oral and written communication (Catts et al., 2002).

Persistent language impairments in early childhood are strong predictors of future reading challenges, even if early signs appear resolved (Stothard et al., 1998). As, some children who seem to recover early still encounter renewed struggles during adolescence, when academic demands increase (Stothard et al., 1998). Letter identification skills in kindergarten have been identified as a key predictor of later reading success, with weak recognition abilities signalling potential reading difficulties(A. G. Bishop & League, 2006). These issues highlight how oral and written language skills are deeply intertwined and emphasize the importance of early assessment and intervention to support long-term academic success.

Longitudinal studies suggest the strong correlation between learning difficulties and reading challenges, highlighting the lasting impact of early language impairments. For instance, research indicates that students with language difficulties in kindergarten are at high risk for developing reading problems by second and fourth grades, which can negatively affect their academic performance (Catts et al., 2002). Evidence further suggests that children whose language abilities improve early are less likely to encounter these reading challenges later on, reinforcing the importance of early intervention (Bishop & Adams, 1990). However, despite early improvements, reading difficulties may re-emerge during middle and high school, as academic demands become more complex, and expectations increase. This finding emphasises the need for long-term monitoring and support to ensure students maintain their progress and succeed throughout their academic journey (Stothard et al., 1998).

Strong reading skills are necessary for high school success, as they help students understand content across multiple subjects (Vaughn & Wanzek, 2014). However, students with learning difficulties often face additional challenges, such as struggles with concentration and a frequent lack of time, which can further hinder their academic performance (Heiman & Precel, 2003). Furthermore, as students' progress through school, the achievement gap often widens due to increasingly demanding assignments (Sáenz & Fuchs, 2002).

Given the persistence of these challenges, traditional education often fails to meet the needs of these students (Amzil et al., 2023). For instance, traditional classrooms generally employ a one-size-fits-all approach, which limits their ability to support students with diverse academic needs (Amzil et al., 2023). While accommodations, such as extended test times, are offered, these are often insufficient (Sokal & Vermette, 2017). Traditional classrooms are often rigid (Pandia et al., 2024) which may increase student stress (Aydin & Demirer, 2022) . Also, their heavy emphasis on grades (Stiggins, 2005) causes students to become more stressed and diverts their focus from learning objectives to performance indicator (DeFeo et al., 2021). Academically challenged students benefit more from visual aids and oral explanations (Heiman & Precel, 2003), while as those without academic difficulties prefer writing while learning (Heiman & Precel, 2003). The hierarchical structure of schools further limits flexibility and personalization, preventing students from receiving the support they need (Pandia et al., 2024). Schools must implement accommodations, such as assistive technologies and personalised support, to help students with learning disabilities (Stetter & Hughes, 2011).

2.6.2 Technology Accommodation in Education

With the limitations of traditional education, technologies can be a powerful tool that would be able to support the students with academic difficulties (Ayasrah et al., 2024) by improving their skills and academic performance. For instance, students with writing difficulties could benefit from speech-to-text programs (Stetter & Hughes, 2011), which allow them to verbalize their thoughts instead of typing or handwriting, easing the burden of spelling and enabling focus on other writing aspects (Gardner, 2018). Similarly, text-to-speech tools assist students with reading difficulties during revision, especially for those with dyslexia, by reducing working memory demands and facilitating more efficient editing (Hebert et al., 2018; Nordström et al., 2019).

For dyslexic students, spelling requires significant cognitive effort, which can limit higher-order writing tasks and lower writing quality (Berninger & Amtmann, 2003). Speech-to-text programs free up cognitive resources, allowing students to focus on idea generation and improving writing quality, though challenges such as adjusting spoken language and ensuring clear speech remain.(Kraft, 2023).

Previous findings suggest that technological accommodations, such as TTS, can contribute to improved academic outcomes for students with learning disabilities (Stetter & Hughes, 2011). TTS increases reading rates, engagement, and comprehension, particularly benefiting students with lower baseline comprehension (Grunér et al., 2018; Moorman et al., 2010). TTS reduces cognitive load for word recognition, enabling students to focus on content comprehension (Meyer & Bouck, 2014),which reduces their frustration while also promoting greater independence and motivation (Edyburn et al., 2005).

Customizing TTS features, such as reading speed and voice type, further enhances performance (Wood et al., 2018). Personalized settings improve reading speed and comprehension for students with academic difficulties (Moorman et al., 2010). Long-term use of TTS leads to lasting improvements in reading comprehension, even after discontinuing the tool (Kennedy et al., 2015).

2.7 Performance, Perception, and Student Satisfaction in Distance Learning Media Use

2.7.1 Learning performance on student satisfaction

Student satisfaction can be defined as the extent to which students' expectations are met regarding their educational experiences (Oliver & Bearden, 1985). Satisfied students tend to be more engaged at school and display lower attrition rates (Gray et al., 2016). In contrast, students whose expectations are unmet are more likely to drop out, particularly during their first year of university (Willcoxson et al., 2011). Moreover, students who feel satisfied with their academic performance are more likely to continue performing well (Grayson, 2004).

Prior research has demonstrated a clear connection between various performance factors and student satisfaction (Limna & Siripipattanakul, 2021). For example, a study found a negative correlation between task completion time and student satisfaction, indicating that students who complete tasks more quickly tend to report higher satisfaction (Dostert, 2011). This relationship is echoed in another study, which revealed that satisfaction declines when students perceive tasks as illegitimate or unnecessarily time-consuming (Fila & Eatough, 2018).

Another finding also discovered that students who engage more actively with their online learning instructor report higher levels of satisfaction with their complete learning experience (Kuo et al., 2014). This suggests that engagement promotes a stronger connection with the material, which positively impacts satisfaction.

Finally, a laboratory experiments showed that task success has a positive impact on satisfaction, as students who complete tasks successfully tend to feel more accomplished and satisfied (Locke, 1965).

2.7.2 Impact of student perception on satisfaction

Students' satisfaction with online educational platforms does not only depend on their performance (Lopez et al., 2024) but also on their perceptions of key factors such as trust (E. A. Khan et al., 2023) and confidentiality (Denise et al.,2019). Therefore, addressing these factors is essential to ensuring student satisfaction.

2.7.2.1 Trust and Student Satisfaction

As previously discussed, trust in an educational tool or platform refers to its perceived reliability and consistency in offering accurate, helpful information (Shin, 2021). Research demonstrates that students are more likely to be satisfied when they perceive their institution and its tools as dependable and accurate, such as when lecture quality corresponds with institutional trust (Martin & Nasib, 2021). Similarly, studies on AI-powered tools, such as chatbots, reveal a positive correlation between students' trust in these tools and their satisfaction. Students who perceive chatbots as reliable report greater satisfaction and are more inclined to engage with them (Pesonen, 2021). These findings suggest that when students have confidence in the reliability if the media they use, their satisfaction with the tool increases.

2.7.2.2 Confidentiality and Student Satisfaction

On the other hand, confidentiality, which reflects students' perceptions of privacy and the protection of their personal information (Sieber, 1992), plays an important role in shaping their satisfaction with online platforms. Research supports this relationship, showing that users' satisfaction with online e-commerce platforms is positively correlated with how they perceive their information to be private (Girsang et al., 2020). Another study found that students felt more satisfied with Facebook when they perceived a high level of privacy, suggesting that confidentiality strongly influences satisfaction (Maqableh et al., 2021).

2.8 Impact of satisfaction on intention to use

Students' intention to continue using educational media platforms is strongly impacted by their level of satisfaction with these tools (Ifinedo, 2018). In this study, intention to use can be defined as "individuals' willingness to accept, reject or continue the use of new technology"(Ajzen, 1985; Venkatesh et al., 2003; Venkatesh & Davis, 2000; Ajzen & Fishbein, 1980). Satisfaction plays a crucial role in promoting students' loyalty, as students are more likely to stick with media that meets their needs and expectations (Ambartiasari et al., 2018). Research supports this, showing that students' loyalty to a platform is significantly affected by how well it satisfies their expectations and objectives (Ambartiasari et al., 2018).

When students perceive a platform satisfying, they are more likely to view it as a beneficial resource and intend to use it repeatedly. For example, a study conducted in Korea during the COVID-19 pandemic found that students highly satisfied with online educational platforms were more inclined to continue using them for future learning (Ambartiasari et al., 2018). This agrees with findings in other contexts: for instance, (Han & Sa, 2022) discovered that users who find a fitness mobile application useful and satisfying are more prone to remain engaged with it, suggesting that satisfaction is a key factor in continued usage.

In summary, the literature highlights the potential of generative AI tools to support students in academic contexts, particularly those with learning difficulties. Richer media modalities, such as voice-enabled AI, have the potential to enhance students' engagement and efficiency (Chen et al., 2020; Stetter & Hughes, 2011). However, significant challenges remain such as concerns regarding trust and confidentiality (Chan & Hu, 2023; Chung et al., 2017). While prior research has examined the general effectiveness of AI tools in education (Luo & Hsiao-Chin, 2023, a notable gap remains in understanding how these tools compare to traditional teacher-student relationships, particularly for students with academic difficulties (Belda-Medina & Kokošková, 2023; Jeon & Lee, 2024; Wang et al., 2024).

This study seeks to bridge the gap by examining the nuanced relationships between media modality, learning performance, and student perceptions. Specifically, it investigates how text-based and voice-enabled generative AI chatbots compared to synchronized text-based teacher interactions in terms of their impact on performance, engagement, and perceptions of trust and confidentiality. By exploring these research questions, this study aims to provide deeper insights into the possible role of generative AI tools in supporting diverse student populations while highlighting key factors to consider for effective implementation in educational contexts.

Chapter 3: Hypothesis development and Proposed Research Model

In this chapter, we will outline the hypotheses developed for this study and establish the research model, exploring how various factors within educational media modalities shape students' experiences. The chapter begins by examining how different levels of media richness impact students' learning performance, which includes task completion time, behavioral engagement, and successful task completion rate. Furthermore, it investigates students' perceptions of trust and confidentiality, emphasizing the relationship between media characteristics and their educational outcomes. This chapter concludes with the presentation of a proposed research model outlining in aggregate the hypothesized relationships between constructs.

3.1 Media Richness on Student Performance

In the previous chapter, we examined how media richness impact the effectiveness of communication and learning. Richer media, which offer greater capability to convey information through multiple cues and channels, have been shown to enhance students' ability to understand and retain information (Shepherd & Marta, 2006). Generative AI tools, particularly in educational contexts, have demonstrated potential for improving engagement by offering interactive and personalized exchanges (Chen et al., 2020; Malik et al., 2019).

Moreover, text-to-speech modalities can provide students with a more fluid and natural way of communicating with educational tools (Abdo et al., 2023), reducing the reliance on typing or word recognition (Bouck et al., 2012). This has been shown to decrease task completion time (Abdo et al., 2023) and alleviate fatigue and frustration (Bouck et al., 2012; Grunér et al., 2018; Moorman et al., 2010), making it easier for students to focus on the content rather than the mechanics of communication.

Building on these insights, we hypothesize that richer media will positively impact students' performance and engagement in the following ways:

- **H1a:** The richer the media the less time it will take students to complete the task.
- **H1b:** The richer the media the more engaged the student will be.

- **H1c:** The richer the media the higher the students' success rate.

3.2 Social Presence on Student Perception

High social presence promotes an emotional connection between students and their learning environment (Sun and Mayer, 2012). It also impacts their perceived trust (Ogonowski et al., 2014) as well as their perceived confidentiality (Champness, 1972). Research has demonstrated that students benefit from the social presence of their instructors, as it contributes to a positive learning environment and enhances their trust in the teacher (Lee, 2007). This connection often leads students to perceive their instructors as reliable and trustworthy sources of information.

In contrast, perceptions of generative AI technologies are more divided. While some individuals remain neutral when asked about their perceived confidentiality in such technologies, others express concerns about confidentiality, fearing that their data might be collected or misused based on their interactions (Chan & Hu, 2023). These concerns suggest that generative AI may struggle to establish the same level of trust and perceived reliability as human instructors.

Building on these insights, we hypothesize the following:

- **H2:** Students will perceive the text-based synchronous chat with a teacher to be more reliable and, therefore, trust it more than the generative AI chatbot with or without voice assistance.
- **H3:** Students will perceive the text-based synchronous chat with a teacher as more confidential than the generative AI tool with or without voice assistance.

3.3 Performance of Students with Academic Difficulties

As discussed in the previous chapter, students with academic difficulties often encounter significant challenges, including struggles with text comprehension, word decoding, and reading fluency (Cortiella & Horowitz, 2014; Fletcher et al., 2012). They also face issues with concentration and time management, which further hinder their academic performance (Heiman & Precel, 2003). Even with accommodations such as additional time during exams, these measures often fall short of addressing their needs effectively (Pandia et al., 2024). Furthermore, reading and academic difficulties are closely associated with school disengagement and higher dropout rates(Williams et al., 2023). Based on these insights, the following hypotheses are proposed.

- **H4a:** Students with academic difficulties will take more time to complete the task compared to students without academic difficulties.
- **H4b:** Students with academic difficulties will be less engaged with the media compared to students without academic difficulties.
- **H4c:** Students with academic difficulties will have a lower successful task completion rate compared to students without academic difficulties.

3.4 Impact of student Performance on their satisfaction

Student satisfaction is closely tied to the extent to which their educational needs and expectations are met (Oliver & Bearden, 1985). Previous research has identified a strong correlation between various factors of student performance and their satisfaction. For instance, shorter task completion times have been associated with higher levels of satisfaction, as students feel more efficient and effective in their learning (Distort, 2011). Similarly, students who successfully complete tasks report feeling a greater sense of accomplishment, which directly enhances their satisfaction (Locke, 1965). Also, active engagement with online learning materials has been shown to positively influence satisfaction, with students who engage more deeply reporting greater contentment with their learning experience (Kuo et al., 2014).

Drawing on these insights, we hypothesize the following:

- **H5a:** Students who spend less time completing the task will report higher satisfaction.
- **H5b:** Students who are more engaged with the media will report higher satisfaction.
- **H5c:** Students who successfully complete the task will report higher satisfaction than those who failed it.

Previous research has identified a correlation between students' perceived trust and their satisfaction, showing that students who view their institution's tools as dependable and accurate report higher levels of satisfaction (Martin & Nasib, 2021). Similarly, studies have found that students feel more satisfied with social media platforms when they perceive their personal information and privacy to be well-protected, emphasizing the role of confidentiality in shaping satisfaction (Maqableh et al., 2021). These findings indicate that trust and confidentiality are distinct factors, each independently influencing students' satisfaction.

Building on these insights, we propose the following hypotheses:

- **H6**: The higher the students' perceived trust in the media type, the more satisfied they will be with it.
- **H7**: The higher the students' perceived confidentiality of the media type, the more satisfied they will be with it.

3.5 Impact of satisfaction on Intention to use

As previously highlighted in the findings, student satisfaction plays an important role in influencing their intentions to continue using a tool or platform. For instance, during the COVID-19 pandemic, students who were highly satisfied with online learning platforms were more prone to use them for future learning (Han & Sa, 2022). Similarly, users of fitness applications who found them satisfying demonstrated higher engagement and ongoing usage (Chiu et al., 2021). Building on this understanding, we propose the following hypothesis:

H8: The higher the students' satisfaction with the media type, the more they will intend to use it.

These hypotheses establish the foundation for our research model, which functions as the conceptual framework guiding this study. The model captures the relationship between media richness, social presence, student performance, perceptions, satisfaction, and intention to use.

3.6 Proposed research model

The proposed research model and accompanying hypotheses (Figure 1) provide a framework to examine the impact of three communication modalities: a text-based chat with generative AI, a voice-based chat with generative AI, and a text-based chat with teacher. While the voice-based chat with generative AI and the synchronized chat with a teacher are considered richer media, the text-based chat with generative AI represents a leaner medium (Daft and Lengel, 1986). Among these, the synchronized chat with a teacher is expected to provide the highest level of social presence, followed by the voice-based chat with generative AI, and lastly, the text-based chat with generative AI (Short et al.1976)

The study evaluates these modalities across three key areas: Performance, including students' behavioural engagement, task completion success rate, and task completion time; Perception, covering students' perceived trust and confidentiality; and Satisfaction and Intention to Use. By examining these factors in the context of media richness and social presence, this study seeks to identify how each communication modality supports students with and without academic difficulties. This research model provides as a foundation for understanding the impact of media type and students' academic level on learning outcomes and preferences.

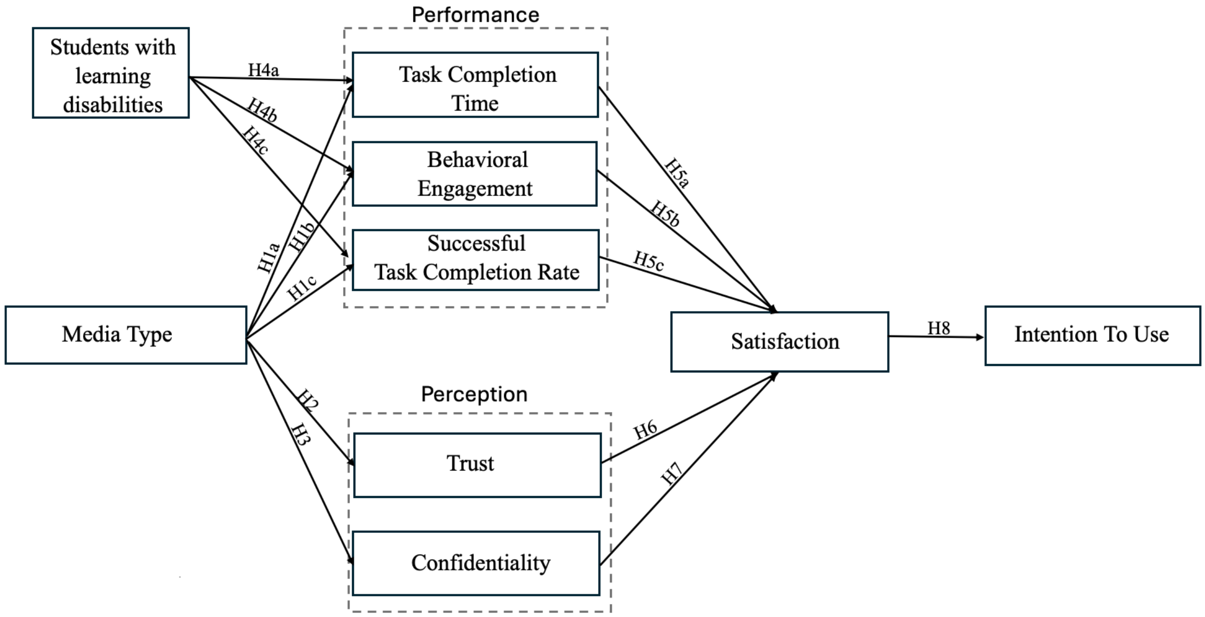


Figure 1 . Proposed Research Model

Chapter 4: Methodology

This chapter outlines the methodology used to investigate the impact of different media types, text-based chat with generative AI, voice-based chat with generative AI, and text-based chat with a teacher, on students' learning performance, perceptions, and satisfaction. The first phase took place in a controlled user experience laboratory, providing a structured environment to monitor and measure participants' interactions under standardized conditions. The second phase was conducted in a school located in North America, offering a naturalistic setting that was more convenient and familiar for the students. This two-phase approach achieved a balance between experimental control and ecological validity.

Key methodological elements include the experimental design, setup, and procedures, such as the sequence of participant activities, tools and environments used, and measures for consistency. Special attention was given to prompt engineering for the generative AI tools, refining prompts to optimize interactions. The chapter also covers participant recruitment, ethical considerations, and strategies to ensure reliability and validity, providing a solid foundation for the results and analyses in subsequent chapters.

4.1 Experimental design

This study follows a 2x3 factorial design within a within-subject experimental framework (Table 2),where the two factors are the student group, students with and without academic difficulties, and media modality, text-based chat with generative AI, voice-based chat with generative AI, and a synchronized text-based chat with a French language teacher. All participants experienced all three modalities, with the order of modalities randomized to minimize potential order bias.

Participants were classified into two groups based on academic level: those identified as academically challenged and those without such challenges. Academically challenged students were defined as those for whom the school had implemented an official academic intervention plan to provide additional support in their learning. Each participant completed the same set of tasks across all three modalities, ensuring consistency in task demands. The tasks are presented in the Appendices (Appendix B)

The manipulation involved two factors: modality type and academic status. This design allowed for a thorough assessment of how these factors affected participants' performance, perceptions, satisfaction, and intention to use the media, examining both main and interaction effects.

The experimental design remained identical for students who conducted the study at school and those who participated in the laboratory. The only distinction was the setting in which the study took place, either a school environment or a controlled laboratory setting.

Table 2. Overview of 2x3 Factorial Design for Media Type and Academic Difficulty Variables

<table>
<tr><td colspan="3" rowspan="3"></td><td colspan="2">Independent Variable</td></tr>
<tr><td colspan="2">Student Academic Level</td></tr>
<tr><td>Students with Academic Difficulties</td><td>Students without Academic Difficulties</td></tr>
<tr><td rowspan="3">Independent Variable</td><td rowspan="3">Media Type</td><td>Text-based chat with generative AI</td><td>Dependent Variable</td><td>Dependent Variable</td></tr>
<tr><td>Voice-based chat with generative AI</td><td>Dependent Variable</td><td>Dependent Variable</td></tr>
<tr><td>Text-based chat with teacher</td><td>Dependent Variable</td><td>Dependent Variable</td></tr>
</table>

4.2 Participants

A total of 37 *Secondary 2* students (22 female, 15 male) aged 13 to 15 (Age mean= 13.14) participated in this study. Seven of them were recruited through social media platforms such as Facebook and LinkedIn, as well as by word of mouth, with data collection conducted at a user experience lab in North America. The remaining 30 students were recruited with the assistance of Alloprof, which facilitated access to a school located in Quebec, Canada. The school granted permission for a two-week period during which their students took part in the study. The study received approval from the Research Ethics Board of our institution (Certificate #2024-5735).

The participants were divided into two groups: a treatment group consisting of students identified as academically challenged, and a control group of students without academic challenges. Of the 37 participants, 22 were identified as having no academic challenges. At the user experience laboratory, a pre-study questionnaire was used to assess eligibility. Participants were asked to report their French grade from the previous year and whether they had an academic intervention plan implemented by their school. This information was used to identify academically challenged students based on school recommendations for academic support. During the data collection at the school, the school administration provided a categorised list, distinguishing between academically challenged and non-challenged students. Participation in the study was voluntary, and students were free to withdraw at any time without providing a reason. Upon completing the study, students received a 30$ gift card to a local library as compensation for their time and effort.

4.3 Experimental Stimuli

During the study, three types of media were used as stimuli: (1) a text-based chat with generative AI (ChatGPT), (2) voice-based chat with generative AI (ChatGPT with voice assistance), and (3) a synchronised text-based online chat with a teacher (using Alloprof's website). Since the study included young children, simpler terms were used to refer to these stimuli: the text-based chat with GenAI was described as the "website with robot", the voice-based chat with GenAI as the "website with robot and voice assistance", and the text-based synchronized chat with the teacher as the "chat with teacher". These stimuli were used to examine differences across two conditions: students with academic challenges and students without academic challenges. Each student used with all three types of media in a randomised order to complete three different French grammatical tasks, which were also randomly assigned. This design guarantees a clear one-to-one match between the stimuli (type of media) and the conditions (students' academic levels), allowing for consistent comparison across the two groups.

4.3.1 Generative AI chatbot

For this study, we trained a generative AI tool, ChatGPT, to function as an educational tutor, simulating a learning environment through interactive conversations. To achieve this, we prompt engineered ChatGPT to align with the instructional framework tailored for Secondary 2 students, focusing on French grammar, spelling, and conjugation (Figure 2). The prompt defined ChatGPT's role not just as an information provider but as a facilitator of learning, employing inquiry-based education methods to engage students effectively.

The prompt specified that the generative AI tool should engage students by asking probing questions and guiding their thought processes without directly giving away answers. This interactive style aimed to enhance learning retention and encourage critical thinking. Key to this was the implementation of constraints: ChatGPT was programmed to redirect students back to the task at hand if they became distracted and to refrain from providing direct answers, thereby promoting students' independent problem-solving skills.

We employed an iterative prompt-engineering process for this study. Throughout the pre-tests, it became clear that continuously refining the instructions within the prompt was essential to maintaining the desired interaction style. By systematically adding details and reinforcing key components of the prompt, we observed a marked improvement in ChatGPT's performance, highlighting the importance of precise and explicit instructions in achieving the intended outcomes.

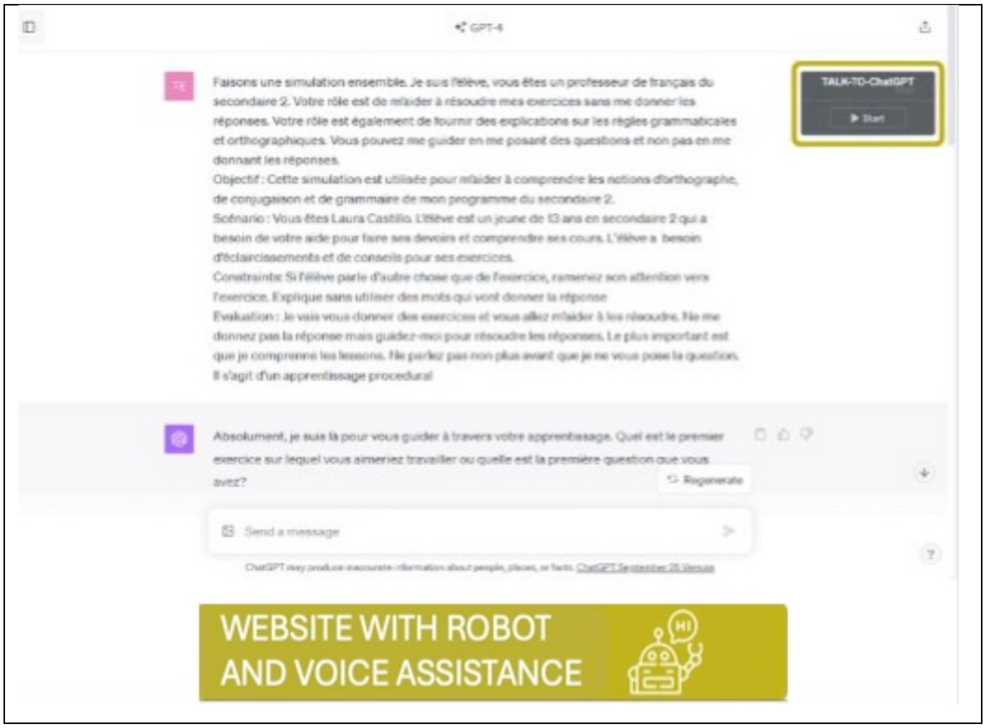
Faisons une simulation ensemble. Je suis l'élève, vous êtes un professeur de français du secondaire 2. Votre rôle est de m'aider à comprendre les différentes notions sur le thème questionné sans me donner les réponses. Votre rôle est également de fournir des explications sur les règles grammaticales et orthographiques. Vous pouvez me guider en me posant des questions et non pas en me donnant les réponses.
Objectif : Cette simulation est utilisée pour m'aider à comprendre les notions d'orthographe, de conjugaison et de grammaire de mon programme du secondaire 2.
Scénario : Vous êtes un professeur de français. L'élève est un jeune de 13 ans en secondaire 2 qui a besoin de votre aide pour faire ses devoirs et comprendre ses cours. L'élève a besoin d'éclaircissements et de conseils pour ses exercices.
Contraints : Si l'élève parle d'autre chose que de l'exercice, ramenez son attention vers l'exercice. Explique sans utiliser des mots qui vont donner la réponse. Ta réponse ne doit pas dépasser les 50 mots. Aussi, n'utilise pas le mot ou le nom ou le verbe qui compose la réponse. Si l'étudiant te dit qu'il ne sais pas la réponse, explique lui d'une autre manière au lieu de lui donner la répose.
Évaluation : Je vais vous donner des exercices et vous allez m'aider à les comprendre. Ne me donnez pas la réponse mais guidez-moi pour résoudre les exercices. Le plus important est que je comprenne les leçons. Ne parlez pas non plus avant que je ne vous pose la question. Il s'agit d'un apprentissage procédural .
Méthode: Je te pose une question sur un sujet, tu vas m'expliquer toute la leçon. Ensuite, tu vas me poser de questions pour que je résous l'exercise. Pose moi une question à la fois.
Lorsque je te pose ma question commence par m'expliquer la leçon de façon générale vers le spécifique avant de me diriger vers les possibles bonnes réponses
Il est plus important que l'élève puisse apprendre à analyser et identifier les possibles réponses qu'à le mener sur la réponse.
Pour la méthodologie d'enseignement, priorisez de poser de questions et interagir avec l'élève uniquement avec ses réponses à la place de lui fournir directement la réponse ou des indices de réponses. reponds en francais

Note. Translation will be provided in the appendices (Appendix A).

Figure 2. Final prompt for configuring the Generative AI Tool, ChatGPT, as an Educational Tutor

4.3.2 Generative AI chatbot with voice assistance

In addition to text-based interaction, this study utilized a voice assistance plugin integrated with ChatGPT on the Google Chrome browser called talk to GPT (Figure 3). This technology facilitated a dual communication mode, where students could communicate with the chatbot through speech, and responses from ChatGPT were read aloud while being displayed on the screen. This setup aimed to mimic a more natural educational interaction and assess the impact of auditory learning cues on student engagement and comprehension. We used the same prompt as for ChatGPT without the voice assistance.



Note. *The same prompt as the text-based generative AI tool was used.*

Figure 3. The Generative AI tool with Voice Assistance Plugin Interface

4.3.3 Synchronised live text chat with a teacher

For the study, we facilitated an online text-based chat between a French teacher and the students, where the teacher guided them and answered their questions on Alloprof's website (Figure 4). The teacher was not physically present in the same room as the student, and the students were unaware of the teacher's identity. All they knew was that they were communicating with a teacher whose objective was to assist them with the assigned tasks.

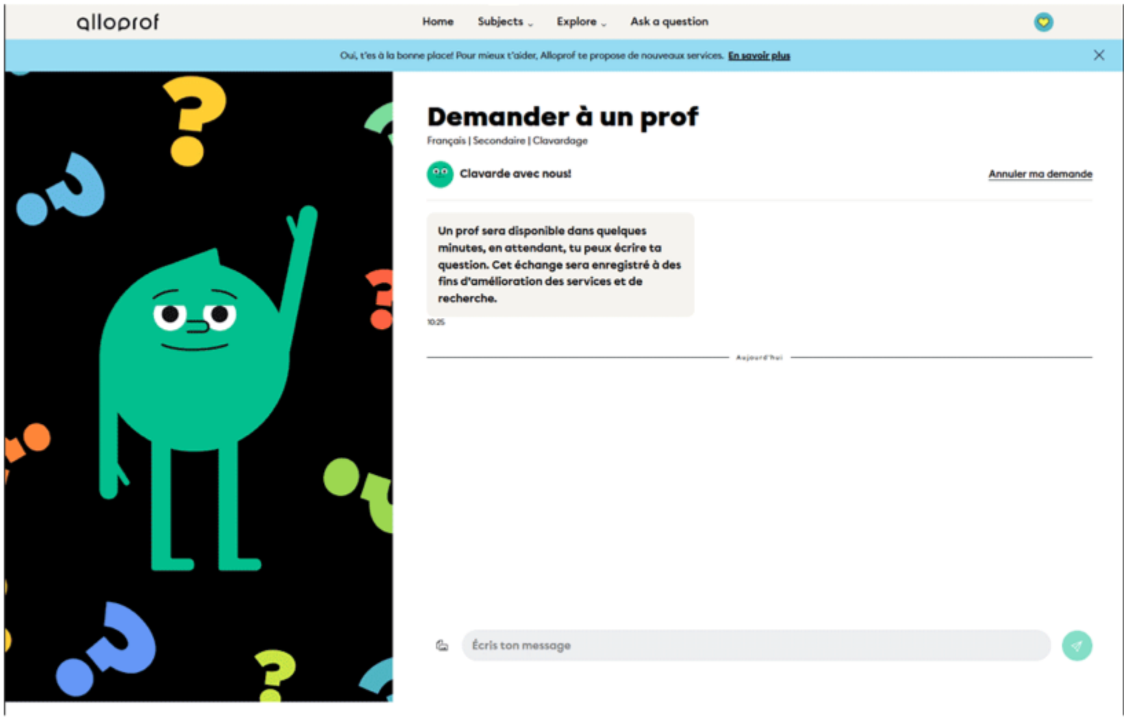
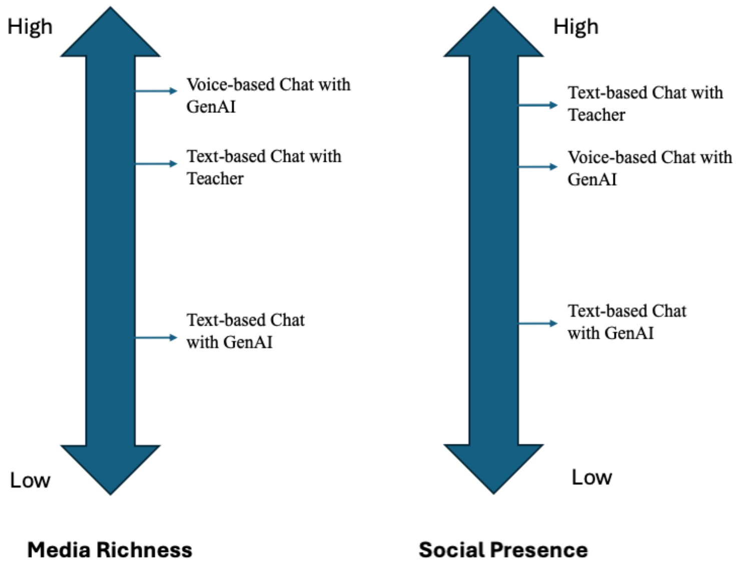


Figure 4. The Synchronized live text chat with a teacher interface

The figure below (Figure 5)illustrates the hierarchy of the three stimuli, text-based chat with generative AI, voice-based chat with generative AI, and a text-based chat with a teacher, in terms of media richness and social presence, based on the finding discussed in the literature review. The left arrow illustrates media richness, where the voice-based chat with generative AI is the richest, followed by the text-based chat with a teacher, with the text-based chat with generative AI as the least rich. On the right side, social presence is displayed, with text-based chat with a teacher ranked highest in social presence, followed by the voice-based chat with generative AI, and lastly, the text-based chat with generative AI. This hierarchy highlights the intended variations in communication depth and interpersonal engagement across the three media types, which are essential factors in analyzing user perceptions and experiences in this study.



Note. This figure is adapted from Daft, et. al (1986)

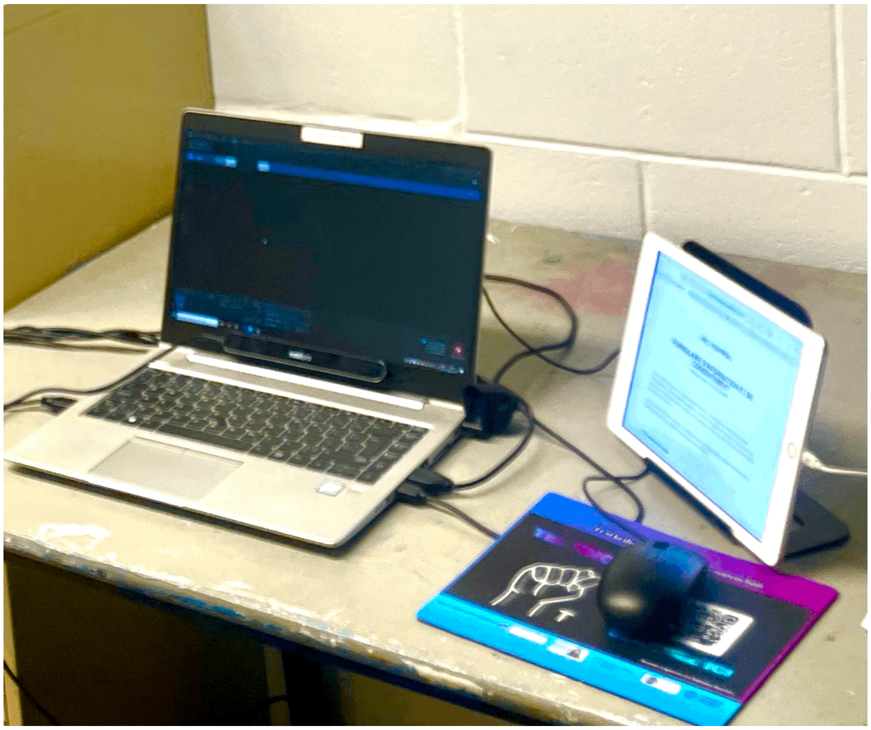
Figure 5. Social Presence and Media Richness Across the Three Media Types Used in Our Study.

4.4 Experimental setup

This multi-device data collection setup involved the use of two devices: a laptop and an iPad 9 (Figure 6). To initiate the session, the moderator opened a tab on their monitor, mirrored to the students' laptops, allowing them to interact with the assigned interface on their laptop. Once the session began, students could freely access and use with the tab to complete their tasks. The tasks and the questionnaire were presented on an iPad positioned approximately 25 cm to the right of the students' laptops. Students also had the option to use a mouse if they preferred.

The devices were carefully positioned at eye level to ensure that students were seated comfortably, without the need to bend or look up to browse the websites. Once students found their answers online using the laptop, they would rotate their bodies to write down their answers on the iPad. Students could utilize with the laptop using the mouse and keyboard, and with the iPad using their fingers.

The laptop, an HP EliteBook 840 with a 14-inch screen and a resolution of 1920 x 1080 pixels, was centrally positioned on the desk. To its right, an iPad Air 2 with a 9.7-inch display and a resolution of 2048 x 1536 pixels was used. You can find in figure 6 the setup of the study.



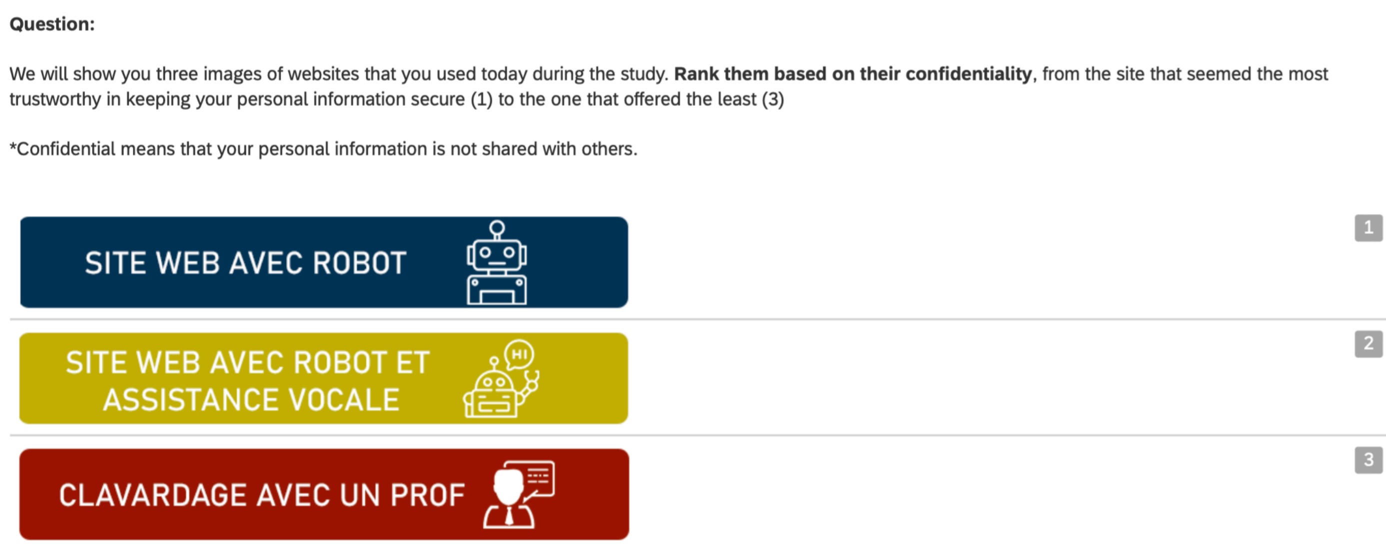
Note. This picture was taken in the school setting. The setup in the school and the User Experience Laboratory were highly similar, ensuring consistency in the study environment.

Figure 6. Study Setup Overview

4.5 Instruments and measures

Some of the measures taken were observational, while others were self-reported. For the observational measures (Table 3), for each participant, the study session recording was uploaded to Observer XT 11 (Noldus Information Technology BV, Wageningen, Netherlands), where we marked the start and end of each task, as well as the points when prompts on ChatGPT were sent. The task number and the type of media used were also considered during the analysis. This approach allowed us to accurately track not only the number of prompts and the time taken to send them, but also the overall time required to complete each task. To measure students' successful task completion rate, we manually evaluated their responses, categorizing each as a success, failure, or partial success. These results were recorded in an Excel sheet for analysis.

Self-reported measures were assessed through post-task satisfaction (Appendix C), using the Satisfaction with Service Scale (Brady et al., 2005), adapted from Voss, Parasuraman, and Grewal (1998). After completing all tasks, students participated in a ranking task where they evaluated the different types of media based on several constructs, including perceived confidentiality, trust, and their intention to use the media (Table 4). We showed participants images of the different websites they used during the study to help them recall their experiences. We then asked them to rank these websites based on their personal experiences with each media. For instance, one of the questions asked them to rank the websites according to their perceived confidentiality (Figure 7) as well as trust and intention to use. The question regarding confidentiality is shown in Figure 7, while the full set of questions addressing all variables, along with their English translations, is provided in the appendices (Appendix D).


Question:

We will show you three images of websites that you used today during the study. **Rank them based on their confidentiality**, from the site that seemed the most trustworthy in keeping your personal information secure (1) to the one that offered the least (3)

*Confidential means that your personal information is not shared with others.

Note. The order of the options presented to the students was randomized across all questions to reduce potential bias in their responses. Questions were presented to the students in French.

Figure 7. High-Ranking Questionnaire Administered at the End of the Study

Table 3. Observational measures used in the study.

Construct	Definition	Measure	Collection Tool	Analysis Tool
Successful Task Completion Rate	The completion of a task without significant errors or deviations from the correct steps, resulting in the desired outcome (Law Insider, n.d.)	Evaluation of student responses as success, partial success, or failure	Qualtrics	Manually coded in Excel
Behavioural Engagement	The number of prompts sent by the student when using the three types of media	Number of prompts	HP Laptop	Observer XT
Task Completion Time	Total duration, measured in seconds, required to complete a single task (Rummel, 2014)	Time taken to complete task	Tobii Pro Nano	Observer XT

Table 4. Self-Reported Measures used in the study.

Construct	Definition	Measure	Scale item
Satisfaction	The extent to which students' expectations are met regarding their educational experiences' (Oliver and Bearden, 1985)	Satisfaction with Service Scale	To what extent do you agree with the following statements regarding the help received? (1= "Strongly disagree" and 7= "Strongly agree") - I am satisfied with the help received. - I am happy with the help received. - I am unhappy with the help received.
Behavioural intention to use	"Individuals willingness to accept, reject or continue the use of new technology" (Ajzen, 1985; Ajzen and Fishbein, 1980; Venkatesh and Davis, 2000; Venkatesh, Morris, Davis and Davis, 2003)	High Ranking Test	Rank the websites based on how likely you are to recommend them to your peers; from the site you would most likely recommend (1) to the one you would least likely recommend (3)
Confidentiality	Consent from individuals regarding how their data may be used (Sieber, 1992)	High Ranking Test	Rank the websites based on their confidentiality, from the one you found most trustworthy in protecting your personal information (1) to the one you found least trustworthy (3)
Trust	The belief that the recommendations and responses of AI or human agents are reliable and credible (Shin, 2021)	High Ranking Test	Rank the websites according to your confidence in the information they provide, from the most reliable (1) to least reliable (3).

4.6 Experimental Procedure

Before arriving at the facility, we obtained parental consent forms for the children's participation in the study. Upon arrival, we explained the study to the participants and secured their consent for participation and the collection of physiological data.

Next, we initiated eye-tracking calibration, instructing students to focus their gaze on specific areas of the screen as directed by the moderator. If calibration results were unsatisfactory, students repeated the process. Participants then completed a pre-study questionnaire on an iPad, which included socio-demographic questions and determined their group classification (academically challenged or not). The moderator conversed with the students about their technology habits and comfort levels, with a note-taker documenting responses, as the study was not recorded.

Following this, students engaged in three tasks, each accompanied by a questionnaire. Upon completing all tasks, they filled out a post-study questionnaire ranking the modalities used. Instructions for each task and corresponding media were displayed on an iPad to the right of the students, while the moderator opened the designated website on the student's laptop. Once ready, the student began the task, recording answers on the iPad. After each task, students completed a related exercise using only the knowledge acquired, without the aid of the website.

To guarantee complete randomization, we created three Qualtrics surveys that randomized both the order of tasks and the sequence of media used. Since the three tasks could be completed in any order and each task was assigned a different modality, this resulted in a total of 36 possible combinations per participant, maximizing the study's reliability.

Subsequently, the moderator conducted interviews to gain further insights into participants' experiences with the media types. After the interviews, students received their compensation, after which they were thanked and dismissed.

4.7 Data Analysis

Utilising SAS version 9.2 for statistical analysis (SAS Institute Inc., Cary, NC, USA), we began by applying descriptive statistics to provide a baseline understanding of the collected data. This was followed by inferential statistical tests to examine relationships between variables. Specifically, a linear regression model with a random intercept was employed to analyse students' task completion time, accounting for non-normal data distribution and intra-subject variability. For behavioural engagement, satisfaction, and successful task completion rate, logistic regression with a random intercept was used, with dichotomous dependent variables. To assess perceived levels of trust, confidentiality, and intention to use, cumulative logistic regression with a random intercept was applied, modelling the probability of lower values for ordinal variables.

Chapter 5: Analysis and Results

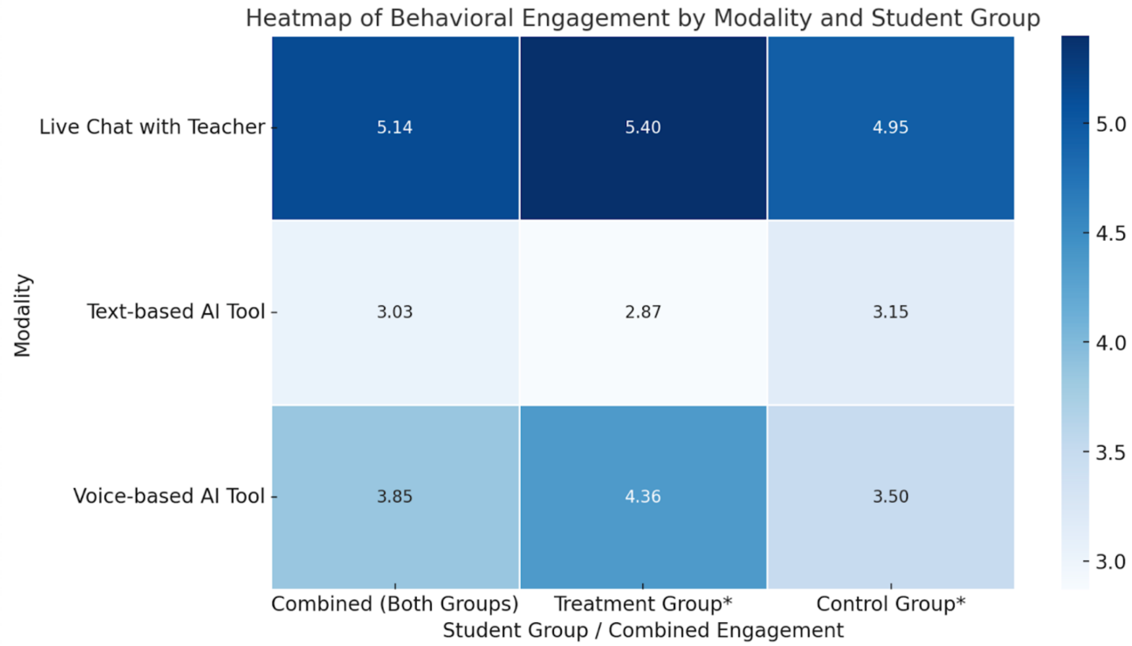
This chapter is structured into three main sections to present the analysis and results of the study. The first section provides descriptive statistics to summarize and offer an overview of the collected data. The second section focuses on hypothesis testing through inferential statistical analysis to evaluate the proposed relationships and effects. Finally, the third section focuses on qualitative analyses, which involved systematically reviewing participants' interactions with the interfaces, analyzing eye-tracking data, and interpreting interview responses from students to deepen the understanding of the quantitative findings.

5.1. Descriptive statistics

Before exploring the inferential analysis, descriptive statistics were computed to summarise the central tendencies and variability within the data (Table 5), providing an overview of the dataset's distribution and key characteristics.

For task completion time, students using the text-based chat with a teacher took the longest (M = 407.03 seconds, SD = 195.34), followed by those using voice-assisted generative AI tool (M = 306.94, SD = 152.91), and text-based chat with generative AI (M = 271.88, SD = 132.20). Comparing students by academic level, those without academic difficulties completed the task faster (M = 282.30 seconds, SD = 152.00) than those with academic difficulties (M = 365.70 seconds, SD = 325.19), indicating that academically at-risk students took significantly longer on average.

For behavioural engagement which presented using the heatmap (Figure 8) students using the text-based chat with a teacher engaged more frequently, using an average of 5.14 prompts (SD = 3.52), compared to the generative AI chat without voice assistance (M = 3.02, SD = 1.96) and with voice assistance (M = 3.85, SD = 2.28). Students without academic difficulties had a mean prompt usage of 3.87 (SD = 2.93), while those with academic difficulties used slightly more prompts (M = 4.20, SD = 2.62).



Note. This figure illustrates students' behavioural engagement across the different modalities; synchronised text-based chat with a teacher, text-based generative AI tool, and voice-based generative AI tool.
*The treatment group refers to the students with academic difficulties.
*The control group refers to the students without academic difficulties.

Figure 8. Dual-Axis Graph of Behavioural Engagement and Successful Task Completion Rate Across Modalities.

The successful task completion rate was highest for the text-based chat with the teacher (M = 0.62, SD = 0.49), followed by the generative AI chat with voice assistance (M = 0.43, SD = 0.50), with the text-based chat with generative AI having the lowest success rate (M = 0.38, SD = 0.49). Students without academic difficulties achieved a higher success rate (M = 0.625, SD = 0.49) than those with academic difficulties (M = 0.267, SD = 0.45).

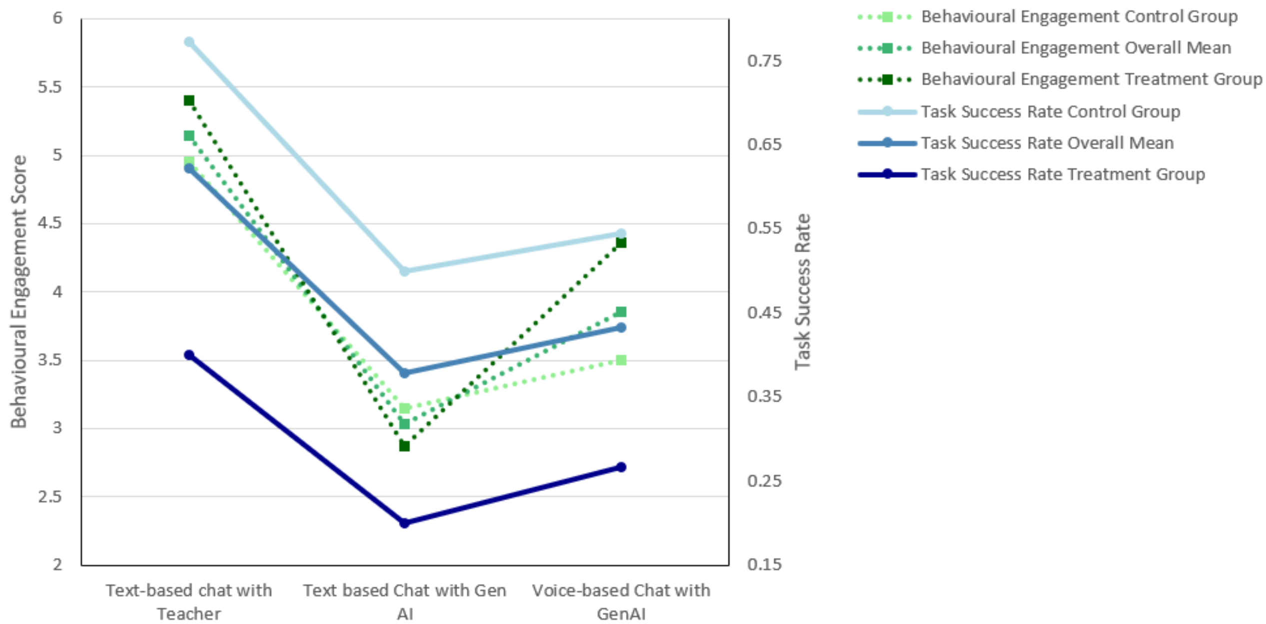
For trust, the text-based chat with the teacher was perceived as the most trustworthy (M = 1.78, SD = 0.75), followed by the generative AI chat without voice assistance (M = 2.97, SD = 0.76), with the generative AI chat with voice assistance receiving the lowest trust ratings (M = 3.68, SD = 0.53). Given that larger values indicate lower trust, the synchronized text-based chat with the teacher was perceived as the most trustworthy, followed by the generative AI chat without voice assistance, and voice-assisted generative AI chat as the least trustworthy. Both students with and without academic difficulties reported similar levels of trust (M = 2.50), with slightly higher variability in the academically at-risk group (SD = 1.1274) compared to those without difficulties (SD = 1.1244).

In terms of confidentiality, the text-based chat with the teacher was perceived as the most confidential (M = 1.51, SD = 0.74), followed by text-based generative AI tool (M = 2.86, SD = 0.73), while voice-assisted chat with generative AI had the lowest perceived confidentiality (M = 3.66, SD = 0.68). Larger values indicate lower confidentiality, confirming the synchronized text-based chat as the most confidential, with voice assisted generative AI chatbot perceived as the least. Both students with and without academic difficulties rated confidentiality similarly (M = 2.5), with minor differences in variability between groups.

For satisfaction, students rated the voice-assisted chat with generative AI the highest (M = 6.24, SD = 0.76), followed by the text-based chat with a teacher (M = 5.83, SD = 1.09), and the text-based generative AI tool (M = 5.36, SD = 1.45) the lowest. Students without academic difficulties reported higher satisfaction (M = 6.01, SD = 1.18) than those with academic difficulties (M = 5.52, SD = 1.30).

Finally, for NPS (Net Promoter Score), students were most likely to recommend voice-assisted chat with generative AI (M = 3.54, SD = 0.73), followed by the text-based chat with a teacher (M = 2.27, SD = 1.02) and text-based chat with generative AI (M = 2.57, SD = 0.83). Students without academic difficulties reported slightly higher NPS scores (M = 2.5, SD = 1.12) compared to those with academic difficulties (M = 2.5, SD = 1.13), with minimal differences in their intention to recommend the media types.

The descriptive statistics also revealed a noteworthy trend: a positive correlation between engagement and success task completion rate (Figure 9)Specifically, the text-based chat with the teacher achieved an average engagement score of (M = 5.143) and the highest task completion rate (M = 0.622). The text-based chat with generative AI had the lowest engagement (M = 3.029) and the lowest task completion rate (M = 0.378). These results suggest a positive relationship between students' engagement and their task success, with higher engagement levels associated with higher completion rates. This finding provides a preliminary insight into the patterns of performance, which is investigated further in subsequent analyses.



Note. The graph shows how engagement levels (primary axis) and task success rates (secondary axis) vary across the text-based chat with a teacher, text-based chat with generative AI, and voice-based chat with generative AI.

Behavioural engagement was measured by counting the number of prompts sent by the students. Successful Task completion rates are represented as proportions ranging from 0 to 1.

*The treatment group refers to the students with academic difficulties.

*The control group refers to the students without academic difficulties.

Figure 9. Relationship Between Behavioral Engagement and Task Success Rates Across Media Modalities

Table 5. Descriptive Statistics of Students' performance, perceptions, Satisfaction, and intention to use of the different modalities.

	Group	Live Chat with Teacher		Text-based AI Chatbot		Voice-based AI chatbot	
		M	SD	M	SD	M	SD
Task Completion Time	Overall	5.89	.51	5.45	.65	5.59	.57
	Treatment Group	6.05	.49	5.38	.87	5.76	.51
	Control Group	5.79	.50	5.49	.49	5.49	.59
Behavioural Engagement	Overall	5.14	3.52	3.03	1.96	3.85	2.29
	Treatment Group	5.4	2.87	2.87	1.81	4.36	2.56
	Control Group	4.95	3.99	3.15	2.11	3.5	2.07
Completion Task Success Rate	Overall	.62	.49	.38	.49	.43	.50
	Treatment Group	.40	.51	.20	.41	.27	.46
	Control Group	.77	.43	.50	.51	.55	.51
Trust	Overall	1.78	.75	2.97	.76	3.66	.53
	Treatment Group	2.13	.96	2.73	.96	3.6	.63
	Control Group	1.55	.51	3.14	.56	3.73	.46
Confidentiality	Overall	1.51	.74	2.86	.73	3.66	.68
	Treatment Group	1.93	.92	2.64	.84	3.50	.94
	Control Group	1.24	.44	3	.63	3.76	.44
Satisfaction	Overall	.43	.50	.38	.49	.65	.49
	Treatment Group	.4	.51	.27	.46	.47	.52
	Control Group	.46	.51	.46	.51	.77	.43
Intention To Use	Overall	2.27	1.09	2.57	.84	3.54	.73
	Treatment Group	2.07	.96	2.60	.91	3.67	.62
	Control Group	2.41	1.05	2.55	.8	3.46	.80

Note. This table presents the means (M) and standard deviations (SD) for task completion time, behavioral engagement, task success rate, trust, confidentiality, satisfaction, and intention to use. The data is segmented by performance, treatment group, and control group across three media modalities: text-based chat with a teacher, text-based chat with generative AI, and voice-based chat with generative AI. In this study, the treatment group refers to the students with academic difficulties and the control group refers to the students without academic difficulties.

*The treatment group refers to the students with academic difficulties.

*The control group refers to the students without academic difficulties.

To conclude, the descriptive statistics provided an inclusive overview of the dataset, highlighting key trends and variability that form the foundation for deeper analysis. Building on these insights, the next section focuses on testing the proposed hypotheses using inferential statistical methods.

5.2 Hypothesis Testing

The Hypotheses subsection evaluates the impact of media type on students' performance, perceptions, satisfaction, and intentions to use. This section presents the results of hypothesis testing, accompanied by a summary table indicating the status of support for each hypothesis (Table 6. Summary of Hypotheses and Their Support Status Also, the research model including path analysis and statistical significance (p-values) of the relationships examined, is illustrated in Figure 13. The results of pairwise comparison tests of all variables are presented in the appendices (Appendix E)

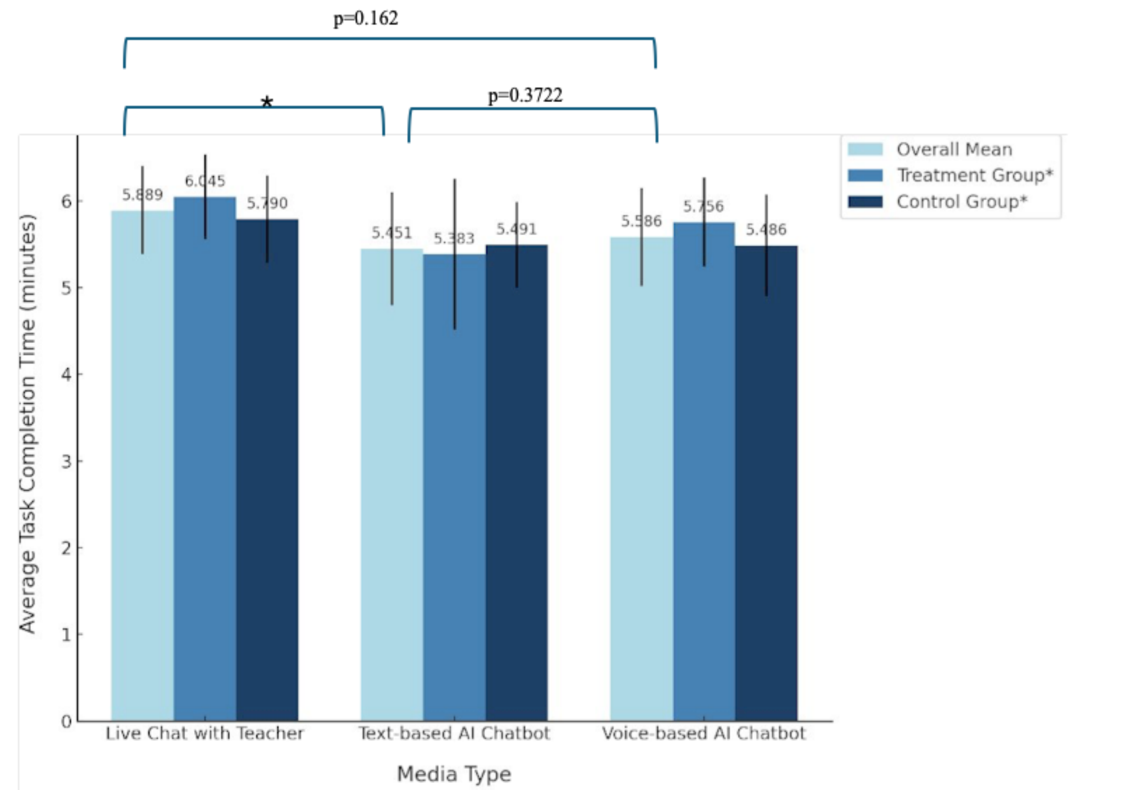
Hypothesis1 (H1):

- **H1a: The richer the media the less time it will take students to complete the task.**
- **H1b: The richer the media the more engaged the student will be.**
- **H1c: The richer the media the higher the students' success rate.**

To analyse the impact of different media types on students' performance, including task completion time, successful task completion rate, and behavioural engagement, specific statistical models were tailored to the nature of the data and the study design. For task completion time, a linear regression model with a random intercept to account for intra-subject variability, given that each student interacted with all three media types was employed. This model was adjusted to account for the non-normal distribution of task completion time, ensuring the reliability of the analysis.

For behavioural engagement and successful task completion rate, a logistic regression model with a random intercept was employed, as both outcomes were dichotomous dependent variables. Behavioural engagement was coded as 1 for engaged and 0 for not engaged, while successful task completion rate was coded as 1 for success and 0 for failure. Given that the distribution of these variables was heavily skewed, logistic regression was appropriate, as it does not assume normality and is well suited for modeling binary outcomes. This approach accounted for repeated measures within subjects and provided insights into the likelihood of success and engagement across different media types.

The results revealed that media type had a significant effect on task completion time, $F(3, 103) = 7.88$, $p < .0001$ (H1a), as illustrated in Figure 10. Post-hoc pairwise comparisons with Holm correction indicated that students spent significantly more time completing tasks in the text-based chat with a teacher compared to text-based chat with generative AI ($M = 0.4276$, $SE = 0.15$), $t(103) = 2.85$, $p = 0.0053$, adjusted $p = .0263$. However, no significant effect of media type was found on behavioural engagement, $F(2, 64) = 1.23$, $p = 0.2979$ (H1b), or on successful task completion rate, $F(3, 103) = 1.51$, $p = 0.217$ (H1c). These findings support hypothesis H1a but do not provide support for H1b and H1c.



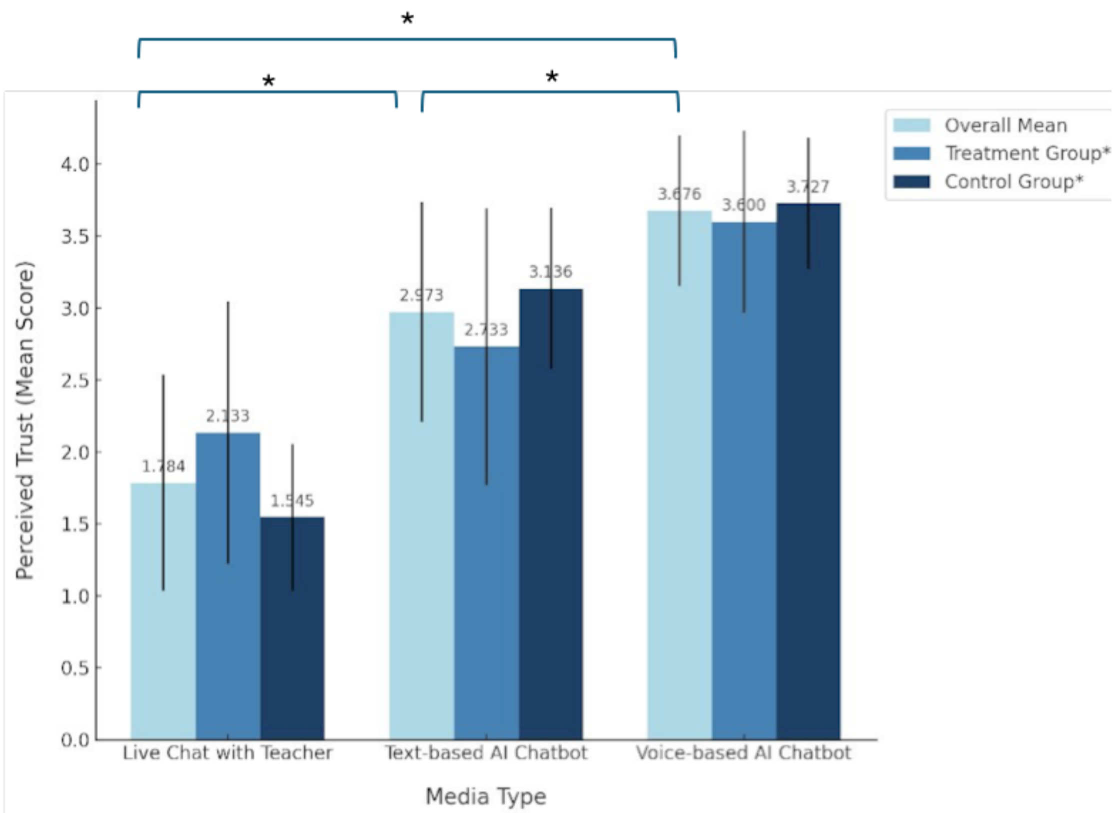
Note. The graph displays the average task completion time (in minutes) across three media types: text-based chat with a teacher, text-based chat with GenAI, and voice-based chat with GenAI. Error bars represent standard error. The overall mean task times, as well as the task times for the treatment group (students with academic difficulties) and the control group (students without academic difficulties), are presented separately. A statistically significant difference ($p < .05$) is indicated with an asterisk. Non-significant p-values are labelled above the comparisons.

Figure 10. Average Task Completion Time by Media Type and Academic Group (with Error Bars).

Building on this, we examined the effect of media types on students' perceptions, specifically their trust and confidentiality, to assess hypotheses H2 and H3.

Hypothesis 2 (H2): The type of media used has a significant effect on students' perceived trust.

To analyse the impact of media type on students' perceived trust, we conducted a cumulative logistic regression with a random intercept model, estimating the probability of lower values for the ordinal dependent variable. As shown in Figure 11, the results indicated a significant effect of media type on perceived trust, $F(3, 101) = 25.9$, $p < .0001$ (H2). Pairwise comparisons revealed that the text-based chat with the teacher was perceived as significantly more trustworthy than voice-based chat with generative AI ($B = 5.0942$, $SE = 0.6552$), $t(101) = 7.77$, $p < .0001$. Also, the text-based chat with generative AI was perceived as more trustworthy than the voice-assisted version ($B = 2.1012$, $SE = 0.5223$), $t(101) = 4.02$, $p = .0001$, adjusted $p = .0002$. The text-based chat with the teacher was also perceived as more trustworthy than the text-based chat with generative AI ($B = 2.993$, $SE = 0.5437$), $t(101) = 5.5$, $p < .0001$, adjusted $p < .0001$.

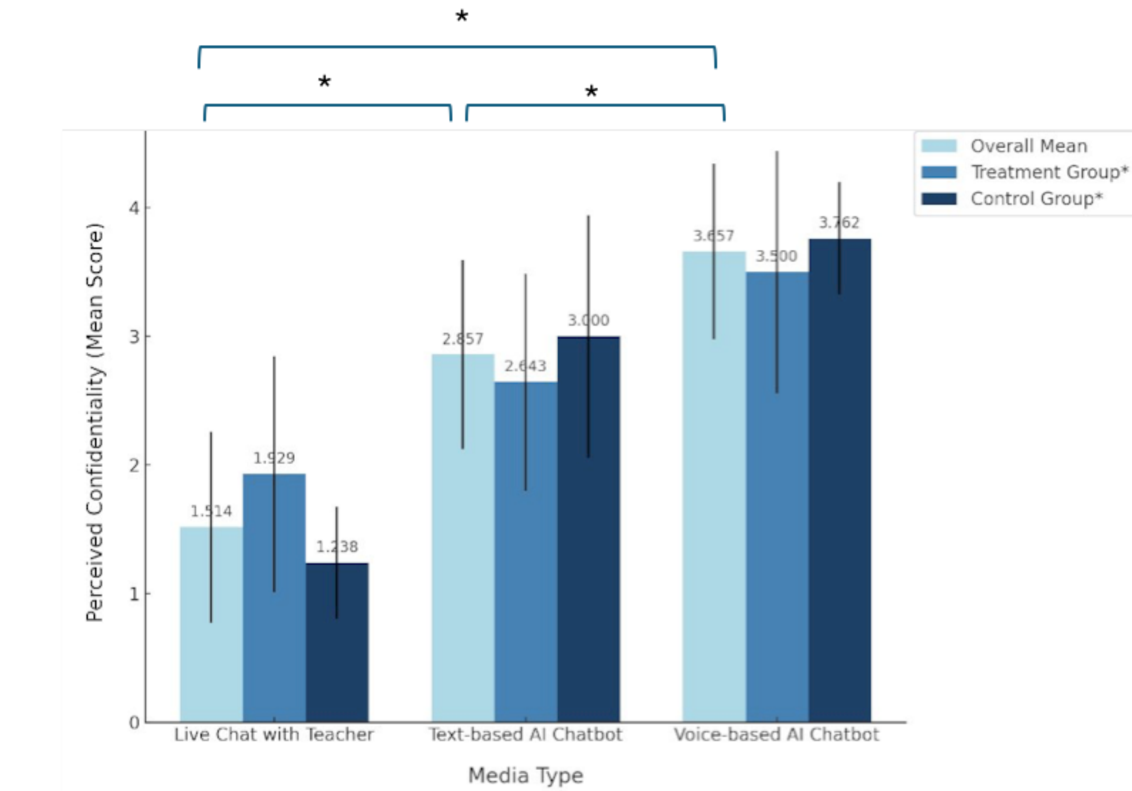


Note. This graph presents the mean scores of students' perceived trust across three media types: text-based chat with a teacher, text-based chat with generative AI, and voice-based chat with generative AI. The data is segmented by aggregate mean, as well as treatment group (Students with academic difficulties), and control group (Students without academic difficulties). Error bars represent standard error. Statistically significant differences ($p < .05$) are marked with asterisks above the corresponding comparisons. Perceived trust was evaluated through a high-rank test, where participants were asked to rank the different modalities based on their trust in each one.

Figure 11. Students' Perceived Trust by Media Type and Academic Group (with Error Bars).

Hypothesis 3 (H3): The type of media has a significant effect on students' perceived confidentiality.

To examine the impact of media type on students' perceived confidentiality, a cumulative logistic regression model with a random intercept was applied as the one used to evaluate perceived trust, estimating the probability of lower values for the ordinal dependent variable. The analysis revealed that media type had a significant effect on perceived confidentiality as visualised in the graph (Figure 12) (3, 95) = 23.31, $p < .0001$ (H3). Pairwise comparisons indicated that text-based chat with the teacher was perceived as significantly more confidential than voice-based chat with generative AI (B = 5.2575, SE = 0.6513), t (95) = 8.07, $p < .0001$. The text-based modality of the generative AI tool was also perceived as more confidential than the voice-assisted version (B = 2.214, SE = 0.5352), t (95) = 4.14, $p < .0001$. Furthermore, the text-based chat with the teacher was perceived as more confidential than the text-based chat with generative AI (B = 3.0435, SE = 0.54), t (95) = 5.64, $p < .0001$. These results support both hypothesis H2 and H3.



Note. The graph shows the mean scores of students' perceived confidentiality across three media types: text-based chat with a teacher, text-based chat with generative AI, and voice-based chat with generative AI. The data is broken down by aggregate mean, treatment group (Students with academic difficulties), and control group (Students without academic difficulties). Error bars represent standard error. Statistically significant differences ($p < .05$) are marked with asterisks above the applicable comparisons. Perceived confidentiality was evaluated through a high-rank test, where participants were asked to rank the different modalities based on their trust in each one.

Figure 12. Students' Perceived Confidentiality by Media Type and Academic Group (with Error Bars).

Hypothesis 4 (H4):

- **H4a:** Students with academic difficulties will take more time to complete the task compared to students without academic difficulties.

- **H4b:** Students with academic difficulties will be less engaged with the media compared to students without academic difficulties.

- **H4c:** Students with academic difficulties will have a lower successful task completion rate compared to students without academic difficulties.

To analyse the impact of students' academic level on performance, we conducted a series of statistical tests tailored to each hypothesis. For task completion time (H4a) and behavioural engagement (H4b), we employed linear regression models with a random intercept to account for intra-subject variability, followed by pairwise comparison tests to examine differences between students with and without academic difficulties. Neither analysis revealed a statistically significant effect of academic level on task completion time ($F\ (1,106) = 0.68$, $p=0.4128$) or behavioural engagement $F\ (1,66) = 0.55$, $p=0.4607$).

For successful task completion rate (H4c), a logistic regression model with a random intercept was used, modelling the probability of task success (coded as 1 for success and 0 for failure). The analysis revealed a significant effect of academic level ($F\ (1,106) = 15.29$, $p=0.0002$), indicating that students without academic difficulties were more likely to succeed. Pairwise comparisons confirmed this finding, with students without academic difficulties showing significantly higher success rates compared to those with academic difficulties ($B=-1.5665$, $SE=0.4006$, $t\ (106) = -3.91$, $p=0.0002$, adjusted $p=0.002$).

These results support H4c, demonstrating a significant difference in successful task completion rates based on academic level, but do not provide evidence to support H4a or H4b.

Hypothesis 5 (H5):

- **H5a: Students who spend less time completing the task will report higher satisfaction.**
- **H5b: Students who are more engaged with the media will report higher satisfaction.**
- **H5c: Students who successfully complete the task will report higher satisfaction than those who failed it.**

A logistic regression model with a random intercept was employed to analyse the impact of students' performance factors, behavioural engagement, successful task completion rate, and task completion time, on their satisfaction. The model estimated the probability of the dependent variable, satisfaction, being equal to 1. Subsequently, we analysed the impact of performance factors on students' satisfaction. The results indicated that task completion time did not exert a statistically significant effect on satisfaction, F (1, 105) = 1.25, p = 0.2662 (H5a), and behavioural engagement also showed no significant effect on satisfaction, F (1, 65) = 0, p = 0.9538 (H5b). However, successful task completion rate significantly predicted satisfaction, F (1, 105) = 4.02, p = 0.0475 (H5c), with higher success rates associated with increased satisfaction (B = 0.7502, SE = 0.3741), t (105) = 2.01, p = 0.0475.

Hypothesis 6 (H6): The students' perceived trust has a significant effect on their satisfaction.

A logistic regression model with a random intercept, modelling the probability of the dependent variable (DV) being equal to 1, was also employed to test the relationship between students' perceived trust and their satisfaction. The results showed that there is no statistically significant relationship between perceived trust and satisfaction, F (1,105) =0, p=0.9959.

Hypothesis 7 (H7): The students' perceived confidentiality has a significant effect on their satisfaction.

To analyse the relationship between students' perceived confidentiality and their satisfaction, the same logistic regression model with a random intercept was applied, modeling the probability of the dependent variable, satisfaction, being equal to 1. The analysis suggests that there is no statistically significant effect of perceived confidentiality on satisfaction F (1,99) =0.43, p=0.5156.

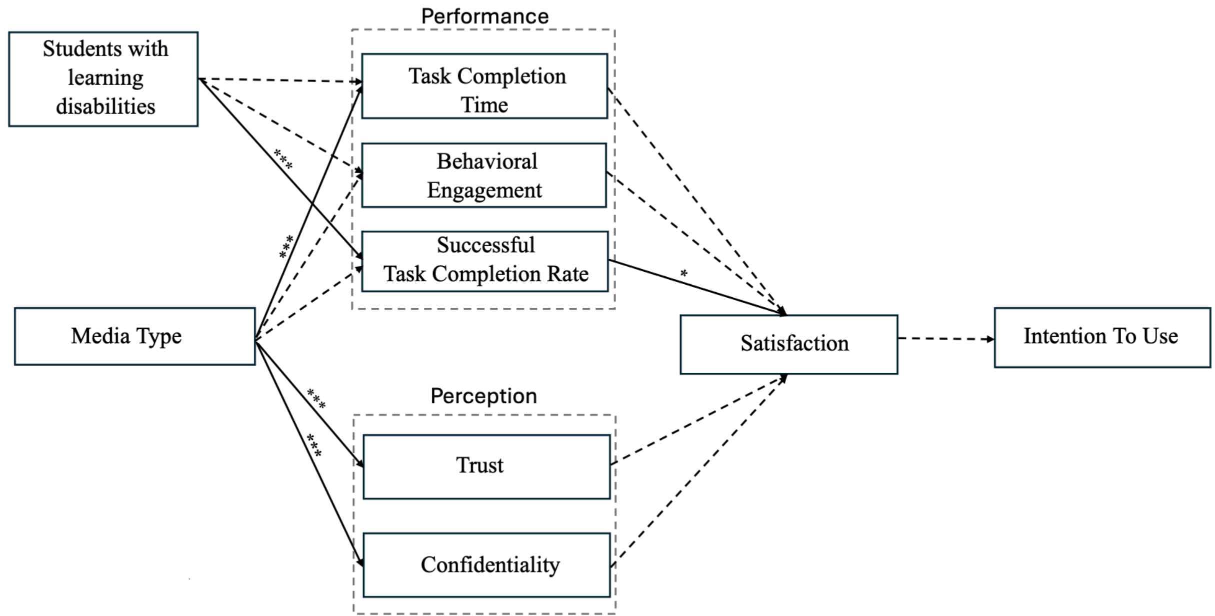
Hypothesis 8 (H8): The students' satisfaction has an impact on their intention to use the media type.

To analyse the impact of students' satisfaction on their intention to use, we employed a cumulative logistic regression model with a random intercept, modelling the probability of the dependent variable, intention to use, taking a lower value. The results did not support hypothesis H7, F (1, 103) = 1.42, p = 0.2362, with an estimate of B = -0.1547, SE = 0.1299, t (103) = -1.19, p = 0.2362.

Table 6. Summary of Hypotheses and Their Support Status

Hypothesis	From	To	$F_{(df1,df2)}$=*F*	*p*	Status
H1a	Type of media	Task Completion Time	F (3, 103) = 7.88	< .0001	Significant
H1b	Type of media	Behavioural engagement	F (2, 64) =1,23	0.2979	Not Significant
H1c	Type of media	Successful Task Completion Rate	F (3,103) =1,51	0.217	Not Significant
H2	Type of media	Perceived Trust	F (3,101) =25,9	<.0001	Significant
H3	Type of media	Perceived confidentiality	F (3,95) =23,31	<.0001	Significant
H4a	Academic level	Task Completion Time	F (1, 106) =0,68	0.4128	Not significant
H4b	Academic level	Behavioural engagement	F (1,66) =0,55	0.4607	Not Significant
H4c	Academic level	Successful Task completion rate	F (1,106) = 15.29	0.0002	Significant
H5a	Task Completion time	Satisfaction	F (1,105) =1,25	0.2662	Not significant
H5b	Behavioural engagement	Satisfaction	F (1,65) =0	0.9538	Not significant
H5c	Successful task completion rate	Satisfaction	F (1,105) =4,02	0.0475	Significant
H6	Trust	Satisfaction	F (1,105) =0	0.9959	Not significant
H7	Confidentiality	Satisfaction	F (1,99) =0,43	0.5156	Not significant
H8	Satisfaction	Intention to use	F (1, 103) = 1.42	0.2362	Not significant

Note. Pair-wise comparison tests are not included in this table.



Note. Significant differences between groups are indicated as follows: ***p<.001, *p<.05. Solid lines represent supported relationships, while dashed lines indicate unsupported relationships.

Figure 13. Research model with path analysis and p-value.

5.3 Post-hoc analysis: Understanding Task Abandonment and Usability Challenges

To further assess how students utilized the different media types, we conducted post-hoc analysis focusing on qualitative methods. The available data was utilized to investigate and better understand task abandonment behaviors, which were observed during the data collection process and appeared to be specifically associated with the generative AI tools. This phase involved a qualitative analysis of eye-tracking data and verbatim responses from student interviews, providing deeper insights into the behavioral patterns and usability challenges faced by students when engaging with text-based and voice-enabled chat with generative AI, as compared to the text-based chat with a teacher.

When using the text-based chat with generative AI, students generally had more positive than negative experiences. Out of 37 students, 19 reported enjoying their interactions with the chatbot due to its efficient teaching methodology, quick responses, and ease of use. However, 11 students expressed negative experiences, citing difficulties in formulating questions, a lack of empathy from the chatbot, overly complex examples and explanations, and responses that were often inadequate or irrelevant to their needs. The remaining students were neutral, stating that their experience with the chatbot was neither positive nor negative.

A notable difference emerged between the two groups of students, those with and without academic difficulties. Among students with academic challenges, 67% reported feeling comfortable with the text-based chat with generative AI and had a positive experience using it. In contrast, 52.23% of students without academic difficulties reported a similarly positive experience.

However, further insights were revealed when we reviewed video recordings and analyzed eye-tracking data from students interacting with the generative AI tool. Students with academic difficulties abandoned tasks more frequently than their peers without such challenges. Two key factors contributed to this behavior.

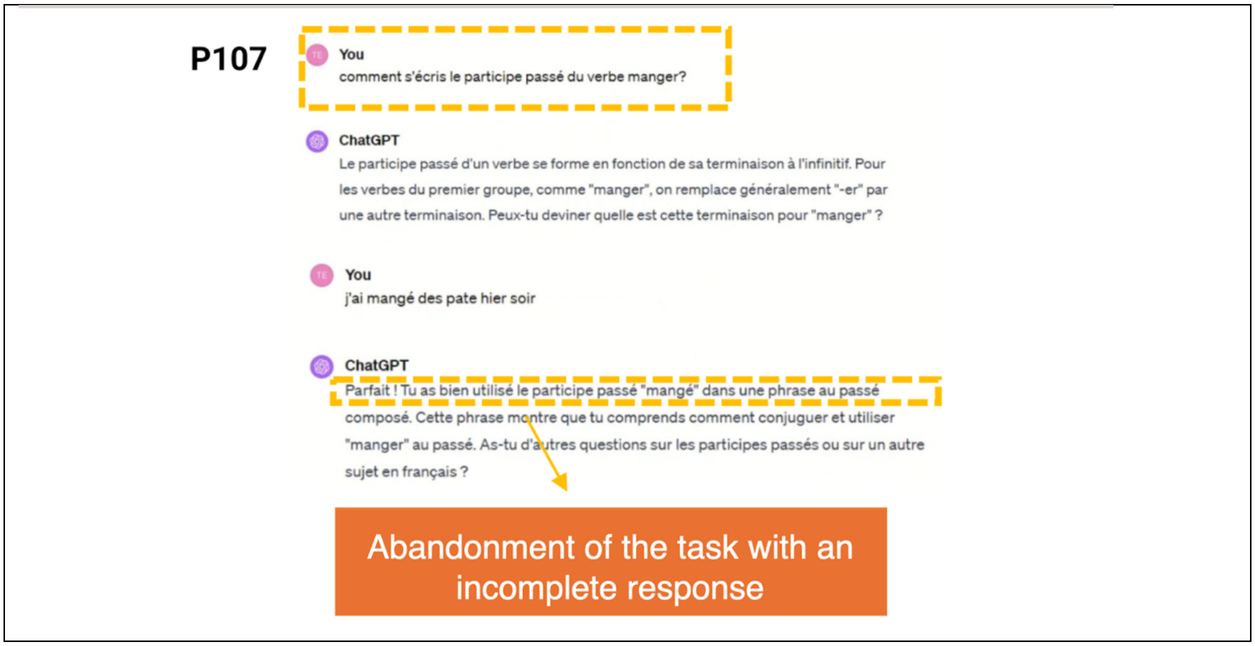
First, these students struggled to formulate precise questions, often receiving vague or unhelpful responses from the chatbot. Without clear guidance, they found it difficult to progress, leading to frustration and disengagement, as shown in **Note.** This figure illustrates a scenario where the student explicitly stated that they did not understand the generative AI tool's answer. Despite the chatbot's attempt to provide further guidance, the student abandoned the task without completing it.

Figure 14. One student described this issue, stating, "I found it wasn't easy to figure out how to use it; it wasn't clear. I didn't know what to write. I didn't know how to phrase the question" (P112).

Second, an important usability issue was uncovered through the eye-tracking data, which showed that students frequently misinterpreted the chatbot's responses. For example, phrases like "*Perfect!*" were often interpreted as confirmation of task completion, even when the response continued with additional instructions or explanations. The eye-tracking analysis revealed that students with academic difficulties tended to focus only on the first part of the chatbot's response before disengaging, as illustrated in Figure 15. This partial reading of the responses contributed to task abandonment and further highlighted the usability barriers faced by students, particularly those with academic difficulties, when engaging with text-based generative AI tools.

Note. This figure illustrates a scenario where the student explicitly stated that they did not understand the generative AI tool's answer. Despite the chatbot's attempt to provide further guidance, the student abandoned the task without completing it.

Figure 14. Task Abandonment Due to Lack of Understanding of the Text-Based Generative AI chat's Response.



Note. The student exited the task immediately after ChatGPT said "perfect," believing the task was complete.

Figure 15. Task Abandonment Due to Misinterpretation of Text-Based Generative AI chatbot Feedback.

Students without academic difficulties also demonstrated task abandonment, though the underlying reasons differed. They were not asking the generative AI tool the right question that would help them effectively resolve the task. Since the generative AI chatbot lacked awareness of the specific task objectives, it could not provide personalized feedback to clarify misunderstandings. Consequently, these students often left tasks unfinished, despite being capable of resolving them with more detailed guidance.

The voice-enabled chat with generative AI also presented additional challenges, particularly for students with academic difficulties. Among the 37 participants who used the voice modality, 30 reported negative experiences. Students noted issues with the system failing to recognize their input on the first attempt, requiring them to repeat themselves. Others highlighted issues with the pace of the voice, describing it as either too slow or too fast, and some noted that the system frequently interrupted them mid-sentence or spoke over them. Additional frustrations included dissatisfaction with the tone of the voice, the overwhelming amount of information provided, and occasional irrelevance or unreliability of responses. Many of these students struggled to articulate their queries in a way that the generative AI tool could process effectively, as shown in the image (**Figure 16**).When their questions were misunderstood or ignored, many became frustrated and abandoned the task without rephrasing or attempting alternative approaches. This frustration is evident in participants' comments. One student expressed, "I didn't like it, really didn't. I said something, and it didn't write what I said, and it was slow to speak. It didn't give me the answers I was expecting to receive" (P115). Another noted, "It didn't listen when I spoke; it talked at the same time as me. It misunderstood the words; I mispronounced something, and it didn't understand. It was easier to just type". (P101). Some students also expressed discomfort using voice commands in the presence of others, such as the study moderator and note-taker, which limited their engagement with this modality. However, despite these difficulties, a few students recognized the potential of the voice-based AI tool to simulate teacher-like conversations. As one participant noted: "It was like with the teacher; I liked it, but I don't know if I'm pronouncing things correctly, and I had to ask several times." (P03).

Note. This figure shows a scenario where the voice-based generative AI tool failed to understand the student on the first attempt, requiring the student to repeat themselves to proceed with the task.

Figure 16. Student Repeats Input Due to Miscommunication with Voice-Based AI Tool.

In contrast, students without academic difficulties showed greater adaptability when using the voice assistant. When the tool failed to comprehend their input, they showed persistence by reformulating their questions multiple times until a satisfactory response was achieved. This ability to adjust their communication strategies enabled them to overcome many of the usability barriers that led to task abandonment in their peers with academic challenges.

These results highlight important behavioural differences between the two groups. Students with academic difficulties were less persistent and more likely to abandon tasks when they encountered challenges. On the other hand, the text-based chat with the teacher, with task-specific knowledge and the ability to provide direct, adaptive feedback, significantly reduced task abandonment and kept students engaged.

In general, the second phase of analyses highlights the usability limitations of the voice-enabled chat with generative AI, particularly for students who may already face difficulties in academic tasks. The inability to provide clear, reliable, and context-appropriate responses contributed to disengagement and task abandonment, as seen especially with certain modalities. The dual-axis graph revealed above (**Figure 9**) revealed a positive correlation between engagement and success levels, emphasizing that higher engagement was associated with better performance. However, task abandonment among students with academic difficulties resulted in lower levels of engagement, which, in turn, contributed to a lower successful task completion rate.

These findings reinforce the need for generative AI tools that are intuitive, responsive, and context aware, with significant improvement in voice recognition and user adaptability. For students with academic difficulties, these tools should be equipped to guide question formulation, and encourage persistence. Tackling these challenges could help mitigate task abandonment and improve the effectiveness of AI tools in educational contexts.

Chapter 6: Discussion

This study aimed to determine whether different levels of media richness affect students' performance, engagement, and perceptions. Specifically, it examined the impact of three media types, text-based chat with a teacher, voice-based chat with generative AI, and text-based chat with generative AI, on students' learning outcomes. The findings revealed that the media type did not significantly affect task completion success (H1c) or behavioural engagement (H1b), though task completion time (H1a) varied, with students taking the longest when communicating with the teacher. This suggests that generative AI tools can match human teachers in supporting student learning while facilitating quicker task completion. However, it was unexpected that students completed tasks more quickly when typing on the generative AI tool compared to using its voice-based modality, as speaking typically requires less time than typing (Sperber et al., 2013). This discrepancy may be explained by usability challenges associated with the voice interface, which could have hindered the students' efficiency and led to longer task completion times.

Although differences in engagement were not statistically significant, students engaged the most with the teacher, followed by the voice-based chat with generative AI, with the text-based chat with generative AI being the least engaging (H1b). This finding has been previously proven as teachers have been proven to positively impact the students' motivations as well as their engagement (Cooper, 2013). Also, many students struggled with the AI interfaces, frequently abandoning ChatGPT due to unclear instructions, reflecting broader trends where users are more likely to disengage from websites when there is a delay in finding the information they seek (Google, 2017). Misinterpretations of ChatGPT's encouraging feedback as task completion further complicated the experience. This issue was particularly pronounced among students with academic difficulties, who often displayed overconfidence, abandoning tasks prematurely. This could be explained by the Dunning-Kruger effect (Kruger and Dunning, 1999), where limited knowledge led the students to believe their responses were correct. In contrast, the teacher's personalised guidance mitigated these challenges by providing clear instructions and redirecting students' focus when they became distracted. This finding corresponds with previous studies showing that students in distance learning often perform as well as, and sometimes even better than, those in traditional face to face settings (Shachar & Neumann, 2003) . However, research also indicates a higher dropout rate among online learners compared to their in-person counterparts (Carnevale, 2000). This trend may originate from the lack of human interaction and emotional connections in virtual settings, which can develop a sense of isolation and disengagement (Rourke et. al, 2001).

This finding partially aligns with MRT (Daft & Lengel, 1986). As the richest medium in this study, the voice-based chat with generative AI improved task efficiency, allowing students to complete tasks faster than the text-based chat with the teacher, consistent with MRT's prediction that richer media reduce ambiguity. However, when examining task success rates, students performed better with the teacher, which is considered lower in media richness than voice-based chat with generative AI. While this finding is not statistically significant, it suggests that AI, although enhancing efficiency, may lack the adaptive, personalised support that human exchanges provide, which may be essential for achieving task success, especially for students needing emotional and relational engagement.

In line with Social Presence Theory, which suggests that a high level of social presence encourages emotional connections that can indirectly impact trust and perceived confidentiality, by making interactions feel more personal, this study found that the students perceived their conversations on the text-based chat with the teacher as more trustworthy (H2) and confidential (H3) than the generative AI tools. The teacher's higher social presence likely strengthened emotional bonds, making the conversation feel more personal. In contrast, the AI modalities, particularly the voice-based chat with generative chat, lacked this level of social presence, which heightened students' privacy concerns. Many students were wary of voice assistants, influenced by rumours of eavesdropping and data misuse, which negatively impacted their perceptions of confidentiality and comfort with the AI interfaces.

Students with academic difficulties faced additional challenges. Although their success rates were lower than those of their peers (H4c), there were no significant differences in their engagement (H4b) or task completion time (H4a). These students struggled to phrase questions correctly, process the AI's responses, and stay motivated, often abandoning tasks prematurely.

These findings highlight the need for accessible and supportive AI tools that cater to students with academic difficulties, ensuring they can benefit fully from these technologies.

Despite these challenges, students reported satisfaction upon completing tasks across all modalities (H5c), suggesting that task success was the primary factor influencing satisfaction. Other factors such as completion time (H5a), engagement (H5b), trust (H6), and confidentiality (H7) did not significantly affect their satisfaction levels. It is important to note the considerable variation in task completion times among students, may explain the lack of a significant effect of task completion time on student satisfaction. This variation could also indicate the presence of a confounding factor, such as differences in persistence levels among students with learning difficulties. These disparities may have influenced the non-significant relationship between media type and task completion time, ultimately impacting satisfaction outcomes.
Interestingly, satisfaction alone did not translate into an intention to use the AI tools again (H8), which contrasts with previous literature. Frustrations with usability, including the need to repeat phrases for voice-based chat with generative AI, difficulties in navigating the tools, and occasional misinterpretation of chatbot responses, likely contributed to both diminished students' satisfaction and reduced their willingness to use these tools in the future. When comparing students' intention to use the different modalities, they demonstrated a stronger intention to use and recommend the text-based chat with the teacher and the text-based generative AI compared to the voice-based modality. This highlights the potential influence of usability challenges on their preferences and intentions.

6.1 Practical Implications

The results point to practical implications that provide actionable guidance for the design, implementation, and policy development of generative AI tools in education. To improve engagement and reduce task abandonment, generative AI systems must evolve to better address the students' needs by providing clearer instructions and more constructive feedback. For instance, replacing vague feedback such as "Perfect" with "That's a good start- here is how you can improve" can guide students more effectively, as well as enhance task focus and completion. Adaptive feedback mechanisms should also be developed to detect when students are confused or distracted, helping them refocus on the task.

To ensure effective usage, generative AI systems should also offer students prompt ideas and detailed instructions. This includes guiding students on how to phrase their queries, examples of questions they can ask, and clear steps for submitting their prompts. Providing such structured support will not only improve usability but also help students, especially those with academic difficulties, fully leverage the capabilities of the AI tool. They should also be equipped with features to identify indicators of confusion or loss of focus, such as extended hesitations or multiple rephrasing of a question. They should actively address these challenges by offering clearer explanations, tailored support, or motivational prompts to guide students back on track and maintain their engagement.

Voice-based AI systems could also benefit from greater customization, allowing students to adjust the tone, speed, and style of the voice to suit their preferences. Improvements in natural language processing would enhance the AI's ability to recognize diverse accents, manage pauses in speech, and secure smooth interactions without interruptions. A more human-like, less robotic voice would develop deeper engagement and make the interaction feel more personal.

The study showcases the importance of preparing students to use the generative AI tools effectively. They should learn not only how to phrase questions correctly but also how to manage the limitations and ethical challenges of these tools, such as the risks of misinformation and plagiarism. Resolving concerns about confidentiality is also important. AI systems should clearly communicate how personal data will be handled, assuring students that their interactions will not be recorded or misused. Incorporating empathetic language and emotional recognition features could further enhance trust, making the AI appear more approachable and human-like. Establishing ethical guidelines on data privacy, transparency, and consent will also promote students' confidence and willingness to use these tools.

These insights potentially suggest that a blended learning model that combines human teachers with generative AI offers a promising way forward. While AI tools can efficiently handle routine educational tasks, teachers play a crucial role in motivating students, providing personalised guidance, and meeting emotional and cognitive needs. This hybrid approach guarantees that students benefit from both the efficiency of AI and the empathy of human exchanges, reducing the likelihood of premature task abandonment.

6.2 Theoretical Contribution

The findings of this study extend MRT by demonstrating that richer media, such as voice-enabled AI, do not always yield better outcomes. Although voice-based AI improved task completion time (H1a), it did not significantly enhance students' behavioural engagement (H1b), trust (H2), or students' intention to use the tools (H8). The frequent task abandonment, caused by unclear instructions and misinterpreted feedback, highlights the limitations of AI tools, especially for students with academic difficulties. These results emphasise the need for more adaptive, user-friendly AI systems capable of providing tailored support to diverse learners. Furthermore, the findings of this study also extend the Social Presence Theory by demonstrating that modalities with higher social presence, such as the synchronized chat with the teacher, result in significantly higher levels of perceived trust and confidentiality compared to leaner modalities.

In conclusion, while generative AI tools such as ChatGPT have the potential to support student learning, significant improvements are required to overcome their current limitations. Usability, emotional intelligence, and trust-building features are essential for making these tools more effective and reliable. Integrating AI with human instruction offers a balanced approach, ensuring that students receive both efficient technological support and meaningful human connection. By resolving the challenges identified in this study, future developments in AI can better meet the needs of all students, especially those with academic difficulties, promoting more inclusive and effective learning environments.

6.3 Limitations and future research

This study has seven limitations, which are natural for an experimental study conducted in a controlled environment and may affect its ecological validity. First, most participants were drawn from the same school, which may have limited the diversity of attitudes, behaviours, and experiences, potentially introducing sampling bias. In addition, because the participants were minors, the scope of data collection was restricted by ethical guidelines, limiting certain types of information we could collect. For example, we relied on self-reported questionnaires to assess perceptions of the media used, rather than more objective physiological measures such as heart rate or galvanic skin response.

Another limitation relates to the high-ranking question used in the final questionnaire, where students were asked to compare the different media directly, rather than evaluating each independently. Also, generative AI's unpredictability posed challenges during the study. For instance, in some cases, we exceeded the daily prompt limit, preventing participants from sending further prompts, and the generative AI tool's responses were sometimes inconsistent across participants. In certain instances, it even asked students for feedback on its responses, which may have impacted perceptions.

Moreover, the tasks that the students conducted were in French, and it remains uncertain whether similar results would occur in other subjects. Additionally, the effect of voice-based interaction could have been influenced by students' lack of familiarity or comfort qith this modality, potentially impacting their experience. Therefore, any differences in the audio chat condition might be due to its novelty rather than the inherent qualities of voice-based interaction.

The presence of a moderator and note-taker could also have contributed to an experimenter effect, where participants may have altered their behaviour due to being observed. Finally, the teacher in the study had an advantage over the AI, as she knew the tasks in advance and was able to redirect students when they lost focus, which AI systems were unable to do.

Finally, another limitation to consider is that generative AI models, such as ChatGPT, the tool used in this study, are continuously evolving, with newer versions being developed and refined. As a result, the learning experience of students may differ with future iterations of these technologies, and this should be considered when interpreting the findings of this study.

For future research, it would be beneficial to involve a more diverse sample by including students from multiple schools or regions, which would help generalise the findings across various educational settings and student populations. Moreover, obtaining parental consent and implementing age-appropriate ethical guidelines could allow for the collection of physiological data (e.g., stress or engagement levels) through non-invasive measures, providing deeper insights into students' reactions.

Future studies should also employ separate evaluations for each modality to capture a more nuanced understanding of how students perceive each medium individually. This could involve using distinct rating scales for key factors such as ease of use, trust, and engagement for each modality. Furthermore, research should examine how generative AI performs across different academic disciplines to determine whether subject matter influences students' academic performance and their perceptions of AI.

Research should continue to explore how newer versions of generative AI impact students' learning experiences over time. Longitudinal studies could track the effects of AI advancements on student performance, perception and satisfaction ensuring that findings remain relevant as these technologies develop. Additionally, comparative studies using different AI models and versions could help determine whether improvements in AI capabilities enhance educational effectiveness or introduce new usability challenges.

To ensure a more balanced comparison between the AI and teacher interactions, generative AI could be pre-programmed with detailed task-specific knowledge, similar to what the teacher possesses. Alternatively, blind studies could be conducted where neither the teacher nor AI has prior knowledge of the tasks, eliminating potential biases.

A longitudinal study could investigate how students' performance, perspectives and intentions toward AI evolve over time, particularly as they become more familiar with the technology. Finally, future research should evaluate each modality independently rather than relying on comparison-based assessments, offering a more thorough analysis of each medium's effectiveness. By addressing these considerations, future research can provide deeper insights into the evolving role of generative AI and its potential to support student learning.

Chapter 7: Conclusion

The objective of this thesis was to assess whether generative AI with voice assistance could help students with academic difficulties overcome their challenges and to compare the effectiveness of text-based and voice-based chat with generative AI systems with text-based chat interactions with a teacher. Using a 2x3 within-subject design, this study explored how different media types with varying levels of media richness and social presence affect students' performance, perceptions, satisfaction, and intention to use. Two central research questions guided this inquiry: first, to what extent generative AI chatbots support the academic performance of students compared to teacher-student interactions, and second, to what extent does generative AI with speech recognition impact the performance, perception, and AI usage intention of students with academic and language difficulties, compared to text-based generative AI.

The findings revealed important insights into the role of generative AI in education. In terms of students' performance, while there was no significant difference in students' successful completion rates and behavioural engagement across the three modalities, task completion time was significantly shorter with text-based generative AI tool than with a text-based chat teacher, indicating that AI can facilitate efficiency without compromising performance. However, students' perceptions highlighted limitations of AI-mediated communication, as the text-based chat with a teacher was perceived as more trustworthy and confidential than the AI systems.

The study highlighted that the subtle differences in how students communicated with each medium provide important insights into their experiences. Behavioral engagement varied based on the clarity and relevance of the guidance offered by each modality. While the generative AI tools adapted their responses to students' input, its limited knowledge of the French material constrained their ability to provide task-specific support. This limitation was further intensified by students often struggling to ask the right questions, making it difficult for the AI to guide them effectively. In contrast, the teacher's strong familiarity with the material enabled them to take the lead in asking students targeted questions, helping them progress toward task completion. This resulted in higher engagement and improved performance in teacher-led exchanges, emphasizing the pivotal role of subject matter expertise and proactive guidance in supporting a supportive and effective learning environment.

Other challenges students encountered with AI-mediated communication reveal important usability issues. The voice-assisted AI frequently failed to understand students' spoken input, leading to frustration, particularly among students with academic difficulties. These students were more likely to abandon the task when the AI misinterpreted their speech or failed to provide relevant responses. This issue was less pronounced among students without academic difficulties, who appeared to adapt better to the challenges posed by the AI tools. Furthermore, students across the board had difficulty phrasing their questions effectively, often struggling to articulate what they needed to ask the generative AI chatbots. This lack of clarity in communication created barriers to productive interaction and hindered the AI's ability to guide them effectively. Also, students often misinterpreted the AI's generic encouraging feedback as confirmation of task completion, a problem less prevalent in the teacher-led interaction, where feedback was clearer and more task-specific. This highlights the need for generative AI systems to provide more precise and constructive guidance to sustain engagement and guarantee accurate task completion.

These findings highlight both the potential and the limitations of generative AI in education. While the tools matched the teacher in terms of successful completion rates and offered efficiency through shorter task completion times, their usability barriers, particularly in voice-assisted interactions, limited their general effectiveness. The results suggest that while media richness and the incorporation of voice assistance enhance certain elements of interaction, their effectiveness is limited by ongoing usability challenges and the lack of task-specific intelligence, which would enable the AI to provide accurate guidance and anticipate students' needs. Overcoming these limitations is crucial to ensuring that generative AI tools provide equitable and effective support for all learners, particularly those with academic challenges.

These findings not only align with but also challenge certain assumptions within MRT and SPT. While richer media (e.g., voice-assisted AI) theoretically should enhance engagement, the absence of nuanced emotional and adaptive feedback limited its effectiveness compared to human interchanges. This suggests that media richness alone is insufficient to promote engagement and success; emotional intelligence and task-specific adaptability must also be considered.

From a theoretical standpoint, this research also contributes to MRT and SPT by situating these frameworks within the context of AI-mediated communication in education. The findings deepen our understanding of how media richness and social presence shape students' learning experiences, leveraging the latest innovations, perceptions of trust, and confidentiality, offering important insights into the intersection of educational technology and communication theories.

Meanwhile, the practical contributions of this study offer insights into how students, with and without academic difficulties, engage with generative AI chatbots, offering the foundation for the development of inclusive and effective educational technologies. These findings help developers and designers create AI tools tailored to diverse learning needs, emphasizing the importance of clear instructions, adaptive feedback, and intuitive interfaces. Generative AI systems should go beyond offering generic responses by providing more precise, constructive, and actionable feedback. Such responses can better guide students toward completing tasks successfully and understanding the material better. Also, AI systems should include mechanisms to detect signs of confusion or disengagement, such as prolonged pauses or repeated attempts to phrase a query, and respond proactively with clarifications, additional guidance, or encouragement to help students refocus and remain engaged.

To ensure students fully optimize their usage of these tools, generative AI systems should also offer prompt ideas, guide users on how to phrase queries effectively, and provide examples of suitable questions. Schools can leverage these insights to guide AI implementation, ensuring these tools enhance learning outcomes while addressing key concerns such as engagement, trust, and confidentiality.

Regarding the usage of voice assistants, enhancements in natural language processing should prioritize recognizing diverse accents, managing pauses, supporting students when they correct themselves, and delivering smoother, interruption-free interactions. Voice-based AI systems could further benefit from customization options, allowing students to adjust tone, speed, and style to suit their preferences, promoting accessibility and engagement. Moreover, ensuring transparency in data handling and integrating empathetic language and emotional recognition features can enhance trust, making interactions with AI systems feel more natural and user-friendly.

Also, the study provides empirical evidence on generative AI's role in supporting students with academic challenges, contributing to theoretical discussions on media richness, social presence and AI's role in education. For technology developers, educators, and instructional designers, it highlights strategies for building adaptable, trustworthy AI systems. Policymakers can use these findings to shape AI-powered educational policies that promote equity and provide inclusive support for all students, particularly those with learning difficulties.

This study has several limitations which may affect its ecological validity. The sample was drawn primarily from a single school, potentially limiting diversity, and introducing sampling bias. Ethical restrictions on research with minors constrained data collection to self-reported questionnaires, excluding objective measures such as physiological responses. The use of direct comparative questions in the final questionnaire may have affected student evaluations. Furthermore, generative AI's unpredictability, including prompt limits and inconsistent responses, introduced variability in the study. The teacher had prior knowledge of the tasks, enabling her to provide adaptive guidance, whereas the generative AI tool lacked task-specific knowledge, which may have affected the comparability of their performances. The presence of a moderator and note-taker may also have caused an experimenter effect.

Future research is essential to build on these findings and handle these limitations. Evaluating each modality independently using specific measures of usability, engagement, and satisfaction could yield a more nuanced understanding of their strengths and weaknesses. Programming generative AI with task-specific knowledge would also enhance its effectiveness, creating a more balanced comparison between AI and teacher interactions. Also, longitudinal studies would be essential to investigate how students' performance and perspectives evolve as they become more accustomed to AI technologies, shedding light on the long-term impact of these tools on learning outcomes. There is also significant potential for developing hybrid educational models that integrate AI with human instruction, leveraging the efficiency of AI and the adaptability of teachers to create richer learning environments. Moreover, as the use of AI in education expands, ethical considerations should remain a priority. Future research should overcome these challenges, offering guidelines to ensure responsible and equitable implementation.

In conclusion, this thesis highlights the transformative potential of generative AI in education, particularly for students with academic difficulties, while recognizing the irreplaceable role of human connection in learning. As AI technologies evolve, they present new opportunities to enhance educational access, engagement, and personalised learning, but their implementation must be guided by trust, ethics, and inclusivity. Achieving a balance, where AI tools complement human interactions, empowers all students, and nurtures meaningful learning experiences, is essential for future education systems.

The findings of this study provide important insights for teachers, technology developers, and policymakers, offering practical guidance on how AI can be integrated responsibly into educational contexts. However, with the rapid pace of technological change, continued research and adaptation are necessary to ensure that AI solutions remain pertinent, equitable, and effective. By building on the contributions of this thesis and pursuing new research directions, future studies will further advance both theoretical and practical understanding of AI in education, promoting innovative, inclusive, and sustainable learning environments.

Appendices

Appendix A- Generative AI prompt translation.

You

Faisons une simulation ensemble. Je suis l'élève, vous êtes un professeur de français du secondaire 2. Votre rôle est de m'aider à comprendre les différentes notions sur le thème questionné sans me donner les réponses. Votre rôle est également de fournir des explications sur les règles grammaticales et orthographiques. Vous pouvez me guider en me posant des questions et non pas en me donnant les réponses.
Objectif : Cette simulation est utilisée pour m'aider à comprendre les notions d'orthographe, de conjugaison et de grammaire de mon programme du secondaire 2.
Scénario : Vous êtes un professeur de français. L'élève est un jeune de 13 ans en secondaire 2 qui a besoin de votre aide pour faire ses devoirs et comprendre ses cours. L'élève a besoin d'éclaircissements et de conseils pour ses exercices.
Contraints : Si l'élève parle d'autre chose que de l'exercice, ramenez son attention vers l'exercice. Explique sans utiliser des mots qui vont donner la réponse. Ta réponse ne doit pas dépasser les 50 mots. Aussi, n'utilise pas le mot ou le nom ou le verbe qui compose la réponse. Si l'étudiant te dit qu'il ne sais pas la réponse, explique lui d'une autre manière au lieu de lui donner la répose.
Évaluation : Je vais vous donner des exercices et vous allez m'aider à les comprendre. Ne me donnez pas la réponse mais guidez-moi pour résoudre les exercices. Le plus important est que je comprenne les leçons. Ne parlez pas non plus avant que je ne vous pose la question. Il s'agit d'un apprentissage procédural .
Méthode: Je te pose une question sur un sujet, tu vas m'expliquer toute la leçon. Ensuite, tu vas me poser de questions pour que je résous l'exercise. Pose moi une question à la fois.
Lorsque je te pose ma question commence par m'expliquer la leçon de façon générale vers le spécifique avant de me diriger vers les possibles bonnes réponses
Il est plus important que l'élève puisse apprendre à analyser et identifier les possibles réponses qu'à le mener sur la réponse.
Pour la méthodologie d'enseignement, priorisez de poser de questions et interagir avec l'élève uniquement avec ses réponses à la place de lui fournir directement la réponse ou des indices de réponses. reponds en francais

Translation to English:

Let's do a simulation together. I am the student, and you are a Secondary 2 French teacher. Your role is to help me understand the different concepts related to the topic being questioned without giving me the answers. Your role is also to provide explanations on grammatical and spelling rules. You can guide me by asking questions and not by giving me the answers directly.

Objective: This simulation is used to help me understand the spelling, conjugation, and grammar rules from my secondary 2 curriculum.

Scenario: You are a French teacher. The student is a 13-year-old in secondary 2 who needs your help to do their homework and understand their lessons. The student needs clarifications and advice for their exercises.

Constraints: If the student is talking about something other than the exercise, bring their attention back to the exercise. Explain without using words that are part of the answer. Your response should not exceed 50 words. Also, do not use the word or verb that makes up the answer. If the student says they don't know the answer, explain in another way instead of giving them the answer.

Evaluation: I will give you exercises, and you will help me understand them. Do not give me the answer but guide me to solve the exercises. The most important thing is that I understand the lessons. Do not go further than what I ask you. This is procedural learning.

Method: I ask you a question about a topic, and you explain the entire lesson to me. Then, you ask me questions to help me solve the exercise. Ask me one question at a time. When I ask you a question, start by explaining the lesson in general terms, and then guide me towards a specific answer before directing me to the possible correct answers. It is more important for the student to learn how to analyze and identify the possible answers than to be led directly to the answer.

For the teaching methodology, prioritize asking questions and interacting with the student only with their responses to the question to guide them towards the correct answer, without providing them with clues to the answers. Respond in French.

Appendix B: Student Task Details- French Exercises

Task1: “Figure de style.”

Q152

Instruction:
Lis l'extrait suivant dans lequel on retrouve une figure de style (**mise en gras**)

- « Ma grand-mère se précipite vers moi dans sa joie contagieuse. Pour attirer mon attention, **elle tape sur mon épaule à répétition, tel un pic-bois.** »

Question: Quel est le nom de cette figure de style?

Pour répondre à cette question, **utilise l'ordinateur à coté de toi.**

Lorsque tu seras prêt.e pour rentrer ta réponse clique sur **"suivant"**

Q55

Quiz:
Lis l'extrait suivant dans lequel on retrouve une figure de style (**mise en gras**)

- « Ma grand-mère se précipite vers moi dans sa joie contagieuse. Pour attirer mon attention, **elle tape sur mon épaule à répétition, tel un pic-bois.** »

Question: Quel est le nom de cette figure de style?

Task 1: Figure de style

post_figuredestyle

Quiz de connaissances:

Identifie dans quelle phrase se trouve la comparaison.

figuredestyle1

1. Lors de notre sortie au parc d'attractions, j'ai pu essayer la grande roue, trois montagnes russes, des jeux d'adresse et le carrousel.
2. La grande roue était plus amusante que le jeu d'adresse.
3. Je pouvais voir toute la ville!

- Phrase 1
- Phrase 2
- Phrase 3

figuredestyle2

1. Les cheveux de ce garçon sont un nuage orageux.
2. Ils ressemblent à un nid d'oiseau.
3. Il est grand temps qu'il aille au coiffeur.

- Phrase 1
- Phrase 2
- Phrase 3

figuredestyle3

1. La chambre de sa sœur est bordélique.
2. Tout traîne par terre.
3. Je n'ai jamais rien vu d'aussi pire que la sienne.

- Phrase 1
- Phrase 2
- Phrase 3

Note. The students completed three tasks in a random order, with the three media types randomly assigned to the task.

Task 2: " Classe de mots"

Instruction:

Identifie la classe de mots du mot en gras de la phrase suivante:

- « Anabelle **se** rend à l'école en autobus tous les jours. »

Pour répondre à cette question, **utilise l'ordinateur à coté de toi.**

SITE WEB AVEC ROBOT

Lorsque tu seras prêt.e pour rentrer ta réponse clique sur **"suivant"**

Saut de page

Q56

Instruction:

Identifie la classe de mots du mot en gras de la phrase suivante:

- « Anabelle **se** rend à l'école en autobus tous les jours. »

postclassedemot

Quiz de connaissances:

Trouve et écrit dans la case le pronom dans les phrases suivantes.

Afficher la discussion (1) Dernier commentaire 26 Oct 2023 7:36am par Sylvain Sénécal

classedemot1

1. L'élève lui donne toute son aide le soir

classedemot2

2. Cette petite fille y ajoute une pièce de monnaie.

Classedemot3

3. Emma a oublié de me donner mes livres.

Note. The students completed three tasks in a random order, with the three media types randomly assigned to the task.

Task 3: "Participe passé"

participe passé

Instructions:
Corrige le participe passé employé avec l'auxiliaire avoir mis en gras dans la phrase suivante:

- « Les pâtes que j'ai **mangé** hier au restaurant étaient si délicieuses que je vais en manger à nouveau ce soir. »

Pour répondre à cette question, **utilise l'ordinateur à coté de toi.**

Quiz:
Corrige le participe passé employé avec l'auxiliaire avoir mis entre parenthèses dans la phrase suivante:

- « Les pâtes que j'ai "mangé" hier au restaurant étaient si délicieuses que je vais en manger à nouveau ce soir. »

PP_ramassé

1. Depuis que les feuilles d'automne sont tombées, personne ne les a **ramassé.**

PP_préferé

2. Quels sont les animaux que tu as **préféré?**

PP_rangé

3. Ils ont **rangé** les valises dans le coffre de la voiture.

Note. The students completed three tasks in a random order, with the three media types randomly assigned to the task.

Appendix C- Post-task Satisfaction questionnaire

Satisfaction-Service

Dans quelle mesure es-tu d'accord avec les affirmations suivantes concernant l'aide reçue? (1="Tout à fait en désaccord" et 7="Tout à fait d'accord")

	1 - Tout à fait en désaccord	2-En désaccord	3-Légèrement en désaccord	4 - Ni en accord, ni en désaccord	5-Légèrement en accord	6-En accord	7-Tout à fait d'accord
Je suis satisfait(e) de l'aide reçue	○	○	○	○	○	○	○
Je suis heureux de l'aide reçue	○	○	○	○	○	○	○
Je suis mécontent de l'aide reçue	○	○	○	○	○	○	○

Translation:

To what extent do you agree with the following statements regarding the help received? (1 = "Strongly disagree" and 7 = "Strongly agree")

- I am satisfied with the help received.
- I am happy with the help received.
- I am unhappy with the help received.

Appendix D- Post tasks questionnaire:

Trust:

Question:
On va te montrer les trois images correspondant aux sites web que tu as utilisés pendant l'étude. **Classe-les selon ta confiance dans les informations qu'ils fournissent**, du plus fiable (1) aux moins fiable (3).

SITE WEB AVEC ROBOT 1

SITE WEB AVEC ROBOT ET ASSISTANCE VOCALE 2

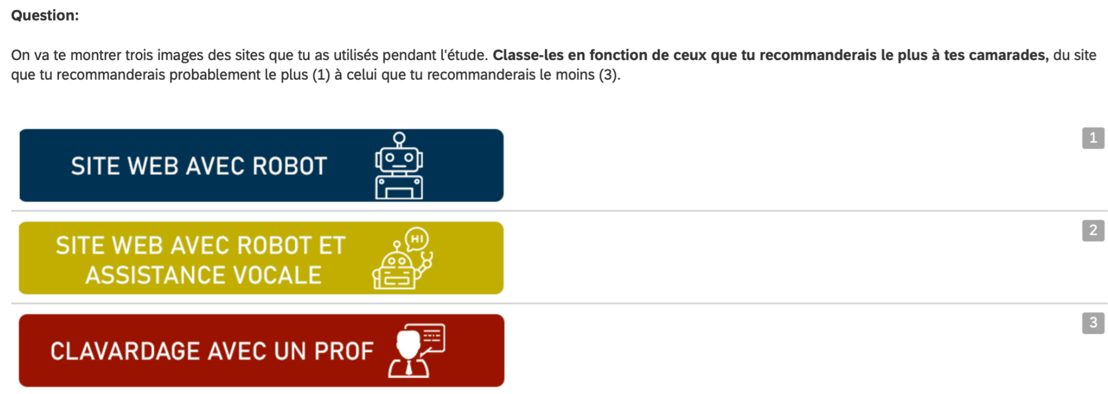
CLAVARDAGE AVEC UN PROF 3

Note: The order of the options presented to the students was randomized across all questions to reduce potential bias in their responses.

Translation:

Rank the websites according to your confidence in the information they provide, from most reliable (1) to least reliable (3).

Intention to use:



Question:

On va te montrer trois images des sites que tu as utilisés pendant l'étude. **Classe-les en fonction de ceux que tu recommanderais le plus à tes camarades,** du site que tu recommanderais probablement le plus (1) à celui que tu recommanderais le moins (3).

SITE WEB AVEC ROBOT 1

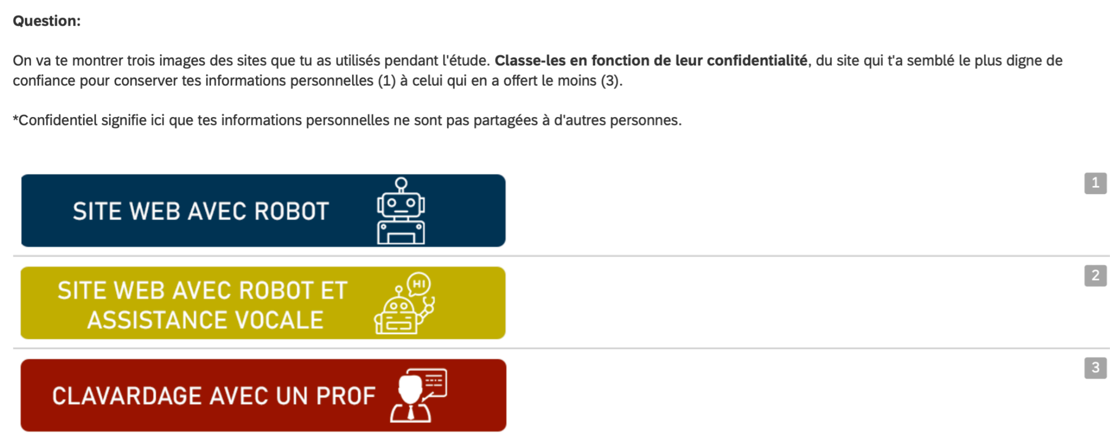
SITE WEB AVEC ROBOT ET ASSISTANCE VOCALE 2

CLAVARDAGE AVEC UN PROF 3

Note: The order of the options presented to the students was randomized across all questions to reduce potential bias in their responses.

Translation: Rank the websites based on how likely you are to recommend them to your peers, from the site you would most likely recommend (1) to the one you would least likely recommend (3).

Confidentiality:



Question:

On va te montrer trois images des sites que tu as utilisés pendant l'étude. **Classe-les en fonction de leur confidentialité**, du site qui t'a semblé le plus digne de confiance pour conserver tes informations personnelles (1) à celui qui en a offert le moins (3).

*Confidentiel signifie ici que tes informations personnelles ne sont pas partagées à d'autres personnes.

SITE WEB AVEC ROBOT 1

SITE WEB AVEC ROBOT ET ASSISTANCE VOCALE 2

CLAVARDAGE AVEC UN PROF 3

Note: The order of the options presented to the students was randomized across all questions to reduce potential bias in their responses.

Translation: Rank the websites based on their confidentiality, from the one you found most trustworthy in protecting your personal information (1) to the one you found least trustworthy (3).

Appendix E: Pairwise comparison Tests for All Variables

Dependent Variable	Effect	Comparison		Estimate	SE	df	T-value	P-value	Adjusted p-value	Status
Task completion time	Media type	Text-based chat with GenAI	Voice-based chat with GenAI	-.14	.15	103	-.9	0.37	0.37	Not Significant
		Text-based chat with teacher	Text-based chat with GenAI	.43	.15	103	2.85	.0053	.03	Significant
		Text-based chat with teacher	Voice-based chat with GenAI	.29	.15	103	1.95	.05	.16	Not Significant
	Academic level	Students with Academic difficulties	Students without Academic difficulties	.11	.14	106	.82	.41	.41	Not Significant
Behavioural engagement	Media type	Text-based chat with teacher	Text-based chat with GenAI	.76	.53	64	1.42	.16	.48	Not Significant
		Text-based chat with teacher	Voice-based chat with GenAI	.05	.52	64	.09	.93	.93	Not significant

Appendix E: Pairwise comparison Tests for All Variables

Dependent Variable	Effect	Comparison		Estimate	SE	df	T-value	P-value	Adjusted p-value	Status
Behavioural engagement	Media type	Text-based chat with GenAI	Voice-based chat with GenAI	-.71	.54	64	-1.32	.19	.48	Not Significant
	Academic level	Students with Academic difficulties	Students without Academic difficulties	.044	.6	66	.74	.46	.46	Not Significant
Successful Task completion rate	Media type	Text-based chat with teacher	Text-based chat with GenAI	1.05	.5	103	2.08	.04	.023	Not Significant
		Text-based chat with teacher	Voice-based chat with GenAI	.67	.5	103	1.36	.18	.88	Not Significant
		Text-based chat with GenAI	Voice-based chat with GenAI	-.38	.5	103	-.75	.46	1	Not Significant
	Academic level	Students with Academic difficulties	Students without Academic difficulties	-1.6	.4	106	-3.91	.0002	.0002	Significant
Trust	Media Type	Text-based chat with teacher	Voice-based chat with GenAI	5.09	.66	101	7.77	<.0001	<.0001	Significant
		Text-based chat with GenAI	Voice-based chat with GenAI	2.1	.52	101	4.02	.0001	.0002	Significant

Appendix E: Pairwise comparison Tests for All Variables

Dependent Variable	Effect	Comparison		Estimate	SE	df	T-value	P-value	Adjusted p-value	Status
Trust	Media Type	Text-based chat with teacher	Text-based chat with GenAI	2.99	.54	101	5.5	<.0001	<.0001	Significant
	Academic level	Students with Academic difficulties	Students without Academic difficulties	.06	.3	104	.19	.85	.85	Not Significant
Confidentiality	Media Type	Text-based chat with teacher	Voice-based chat with GenAI	5.26	.65	95	8.07	<.0001	<.0001	Significant
		Text-based chat with GenAI	Voice-based chat with GenAI	2.21	.54	95	4.14	<.0001	<.0001	Significant
		Text-based chat with teacher	Text-based chat with GenAI	3.04	.54	95	5.64	<.0001	<.0001	Significant
	Academic level	Students with Academic difficulties	Students without Academic difficulties	.06	.32	98	.2	.84	.84	Not Significant

Appendix E: Pairwise comparison Tests for All Variables

Dependent Variable	Effect	Comparison		Estimate	SE	df	T-value	P-value	Adjusted p-value	Status
Satisfaction	Media Type	Text-based chat with teacher	Text-based chat with GenAI	.34	.51	103	.66	.51	1	Not Significant
		Text-based chat with teacher	Voice-based chat with GenAI	-.97	.52	103	-1.88	.06	.25	Not Significant
		Text-based chat with GenAI	Voice-based chat with GenAI	-1.3	.53	103	-2.48	.0147	.09	Not Significant
	Academic level	Students with Academic difficulties	Students without Academic difficulties	-.92	.47	106	-1.96	.05	.05	Not Significant
Intention to use	Media Type	Text-based chat with GenAI	Text-based chat with teacher	-.53	.43	101	-1.22	.22	.22	Not Significant
		Voice-based chat with GenAI	Text-based chat with teacher	-2.56	.5	101	-5.15	<.0001	<.0001	Significant

Appendix E: Pairwise comparison Tests for All Variables

Dependent Variable	Effect	Comparison		Estimate	SE	df	T-value	P-value	Adjusted p-value	Status
Intention to use	Media Type	Text-based chat with GenAI	Voice-based chat with GenAI	2.03	.48	101	4.19	<.001	<.001	Significant
	Academic level	Students with Academic difficulties	Students without Academic difficulties	.06	.31	104	.19	.85	.85	Not Significant

Notes. The estimate refers to the mean difference between group means. Adjusted p-values were calculated using Holm method to account for multiple comparisons.

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