Examining the Determinants of Perceived Effectiveness in AI-powered Conversational Interfaces: A Study Based on Higher Education Sector in Sri Lanka

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ABSTRACT

This study was carried out with the main purpose of identifying the determinants of perceived effectiveness in AI-powered conversational interfaces in higher education in Sri Lanka. There were minimal research being done to analyze the determinants of perceived effectiveness in AI-powered conversational interfaces which reflected a clear literature gap. Further, none of the studies were focused on the AI-powered conversational interfaces in Sri Lankan education institutions. This was identified as the main research problem to carry out this study. A comprehensive literature review was done to identify the main independent variables. These were recognized as Usage Frequency of AI Interfaces, Quality of AI Interaction, Training and Familiarity with AI, and Institutional Support for AI Integration. The dependent variable was identified as the perceived effectiveness in AI-powered conversational interfaces. The theories such as Constructivism and Social Constructivism, Cognitive Load Theory, Connectivism and Behaviorism and Feedback Mechanisms were examined under theoretical review of this study. This study is based on the positivism philosophy and deductive approach to achieve the objectives. Main research instrument used in this study is the survey questionnaire based on a Likert scale. Based on the literature, conceptual framework and hypotheses were developed. A questionnaire was distributed among university students and 100 answers were considered as the sample size. The collected data was analyzed using SPSS software. First, reliability and validity was tested to ensure that the data set is accurate and reliable. A thorough analysis of variables was done using descriptive statistics, and correlation analysis was used to analyze the relationship between the variables. The results indicated that all the identified independent variables have a significant positive correlation with the perceived effectiveness in AI-powered conversational interface. Main implications of these findings are investment in training to enhance students' and faculty's familiarity with AI technologies, improving quality of the interface, support for the integration of AI technologies into the curriculum and encouraging regular usage of AI interfaces. Future researchers may do a longitudinal study covering larger sample sizes to gain better understanding about the perceived effectiveness in AI-powered conversational interfaces in educational institutions.

Keywords; Institutional Support, Perceived effectiveness, Quality of AI Interaction, Training with AI, Usage Frequency

INTRODUCTION

In recent years, the integration of artificial intelligence (AI) into various facets of our lives has been nothing short of transformative. One of the most promising and rapidly evolving domains within AI application is education. This research embarks on a comprehensive exploration into the realm of AI-powered conversational interfaces, specifically chatbots and virtual assistants, and their pivotal role in reshaping higher education. This introduction sets the stage for the ensuing discussion, elucidating the background of AI in education, articulating the research objectives, elucidating the scope and significance of the study, and outlining the structure of the paper.

Background of AI in Education

The roots of AI in education can be traced back to the mid-20th century when scholars began to ponder the possibility of using computers as instructional tools (Natale & Ballatore, 2020). Over the decades, AI technologies have progressively matured, fostering a paradigm shift in education. The advent of machine learning, natural language processing (NLP), and data analytics has ushered in an era where AI-powered tools can not only assist educators but also provide personalized learning experiences to students (Roslan & Ahmad, 2023). As digital natives populate higher education institutions, the integration of AI has become almost inevitable. The inception of AI in education can be attributed to the pioneering work of researchers like B.F. Skinner, who explored programmed instruction and behaviorist principles in the 1950s. Skinner's ideas laid the foundation for early computer-based educational systems, which were rudimentary but showed promise in delivering personalized instruction.

However, it wasn't until the 1980s and 1990s that AI technologies began to gain more traction in education (Doroudi, 2022). Expert systems, a type of AI that emulated the decision-making abilities of human experts, found applications in intelligent tutoring systems. These systems could provide students with feedback and guidance tailored to their individual needs, marking a significant advancement in personalized learning.

The emergence of machine learning and neural networks in the late 20th century ushered in a new era for AI in education. These technologies enabled the development of intelligent agents capable of adaptive learning, natural language understanding, and data-driven insights. As computing power increased, and data became more accessible, AI-powered educational tools became more sophisticated.

One of the notable breakthroughs in recent years has been the integration of AI-driven chatbots and virtual assistants into educational environments. These conversational interfaces can provide students with instant support, answer questions, offer recommendations, and even facilitate administrative tasks. They are designed to enhance the overall educational experience by providing timely and personalized assistance.

Additionally, the field of educational data analytics has gained prominence. AI algorithms can analyze vast amounts of educational data, including student performance, engagement metrics, and learning patterns. This data-driven approach allows educators and institutions to identify areas where students may struggle, adapt teaching methods, and make data-informed decisions to improve learning outcomes.

As the digital generation enters higher education, AI's role is expanding beyond the classroom. Virtual reality (VR) and augmented reality (AR) are being used to create immersive learning experiences. AI-powered content recommendation systems help students discover relevant educational materials. Furthermore, AI can assist in the assessment and grading process, reducing the administrative burden on educators (Jumani et al., 2022).

When analyzing previous literature, it was identified that there are several studies done to analyze the AI-powered conversational interfaces in education, e-commerce, and different other formats (Balakrishnan & Dwivedi, 2021; Ruan et al., 2021; Ashfaq et al., 2020). However, those studies have not captured the determinants of perceived effectiveness of those chatbots. Therefore, this study answers the research question of “What are the determinants of perceived effectiveness in AI-powered conversational interfaces in higher education?”.

In summary, the integration of AI in education has evolved from early experiments to a transformative force in higher education. The convergence of AI technologies, big data, and digital platforms is reshaping teaching and learning, making education more adaptive, personalized, and accessible to learners of all backgrounds. AI's journey in education is ongoing, promising continued innovations in the years to come. Hence this study is done with the main purpose of identifying the determinants of perceived effectiveness in AI-powered conversational interfaces in higher education in Sri Lanka.

Research Objectives

This study has several overarching objectives:

- To investigate the current landscape of AI-powered conversational interfaces in higher education.
- To assess the effectiveness of chatbots and virtual assistants in enhancing student engagement and learning outcomes.
- To examine the perceptions and attitudes of students and educators towards AI in education.
- To identify the challenges and ethical considerations associated with the adoption of AI-powered conversational interfaces in academia.

- To provide recommendations and best practices for the responsible implementation of AI in higher education.

Scope and Significance of the Study

The scope of this study encompasses a wide range of AI-powered conversational interfaces employed in higher education, including but not limited to chatbots, virtual teaching assistants, and automated grading systems. It delves into both the technical aspects of these AI applications and their pedagogical implications. Moreover, it explores the significance of AI in addressing the evolving needs of higher education institutions, especially in a world marred by unprecedented challenges such as the COVID-19 pandemic.

The significance of this study lies in its potential to inform educators, administrators, policymakers, and technologists about the multifaceted impact of AI on higher education. By critically evaluating the effectiveness of AI-powered conversational interfaces, this research contributes to the ongoing discourse on improving the quality and accessibility of education in the digital age.

LITERATURE REVIEW

Evolution of AI in Education

Artificial intelligence (AI) has made remarkable strides in education, transforming traditional learning paradigms and ushering in an era of personalized, efficient, and effective education. The evolution of AI in education can be traced through various stages, each marked by significant technological advancements and educational reforms.

Early AI in Education: Early experiments in AI for education date back to the mid-20th century when computer-based systems were first employed as instructional tools. One notable pioneer, B.F. Skinner, introduced programmed learning, a behaviorist approach, in the 1950s, where students interacted with computer programs to reinforce learning outcomes (Hof, 2018). These early attempts, though rudimentary by today's standards, laid the groundwork for AI's role in education.

While these early attempts may seem rudimentary compared to today's sophisticated AI applications, they set the stage for the integration of technology in education and the exploration of AI's potential (Echezona & Ojukwu, 2023).

Intelligent Tutoring Systems (ITS): The 1970s ushered in a pivotal era in the evolution of AI in education with the emergence of Intelligent Tutoring Systems (ITS). These systems represented a substantial leap in the application of AI technologies to the field of education (De Luise, et.al. 2023).

Key features of ITS included:

Personalization: ITS utilized knowledge representation techniques to create a model of each individual learner. This model allowed the system to understand the learner's strengths, weaknesses, and learning preferences.

Adaptive Content: Leveraging machine learning and AI-driven algorithms, ITS systems dynamically adapted the content and pace of instruction to suit the specific needs of each student. This adaptability ensured that learners received targeted guidance and challenges appropriate to their skill levels.

Immediate Feedback: ITS provided real-time feedback to students, offering explanations and corrections when they made errors. This immediate feedback mechanism was instrumental in facilitating active learning and addressing misconceptions promptly.

Tracking Progress: These systems were capable of tracking each student's progress, identifying areas where they struggled, and offering additional practice in those specific areas.

Data-Driven Insights: The data collected by ITS not only benefited students but also provided educators with valuable insights into student performance and areas of improvement.

Natural Language Processing (NLP) and Chatbots: Advancements in natural language processing (NLP) in the late 20th century opened new horizons for AI in education. Chatbots and virtual assistants, powered by NLP algorithms, started to play a pivotal role in facilitating student-teacher interactions. For instance, ALICE (Artificial Linguistic Internet Computer Entity), was an early AI chatbot that engaged in text-based conversations, answering questions and providing information (Kasthuri & Balaji, 2023).

Big Data and Learning Analytics: The advent of big data and learning analytics in the 21st century marked a turning point in AI's impact on education. The accumulation of vast amounts of educational data, including student performance, interactions, and preferences, enabled the development of predictive models to enhance educational outcomes. Learning management systems (LMS) and educational technology platforms leveraged AI-driven analytics to offer personalized recommendations and insights to learners (Aldahwan & Alsaeed, 2020).

The Rise of AI-powered Chatbots in Higher Education: In recent years, AI-powered conversational interfaces, particularly chatbots, have gained prominence in higher education.

These chatbots, equipped with NLP, machine learning, and voice recognition capabilities, offer students and educators personalized assistance, course information, and administrative support (Rudolph et al., 2023). They have become integral in addressing common student queries, enrollment processes, and providing 24/7 support.

The COVID-19 Pandemic as a Catalyst: The COVID-19 pandemic accelerated the adoption of AI in education. With the sudden shift to remote and hybrid learning models, institutions turned to AI-driven tools, including chatbots, to bridge gaps in online education. These chatbots played a critical role in maintaining communication, guiding students through the transition, and monitoring their well-being (Taylor et al., 2023).

In summary, the evolution of AI in education has seen a progression from early experiments in computer-based learning to the emergence of Intelligent Tutoring Systems, NLP-powered chatbots, and the use of big data and learning analytics. The recent surge in AI-powered chatbots, further accelerated by the pandemic, signifies a new chapter in education.

Theoretical Framework of AI-Powered Conversational Interfaces

To understand the transformative potential of AI-powered conversational interfaces in education, it is essential to ground our discussion in relevant theoretical frameworks that guide the development, deployment, and assessment of these technologies. Several theoretical perspectives inform the design and application of AI-powered conversational interfaces in educational contexts.

Constructivism and Social Constructivism: One foundational theoretical perspective in the application of AI in education is constructivism (Quoc & Van, 2023). Constructivist theories posit that learners actively construct their knowledge through interactions with the environment and that learning is most effective when it is learner-centered and experiential. Social constructivism, an extension of constructivism, emphasizes the role of social interactions in cognitive development. AI-powered conversational interfaces align with these theories by providing personalized, interactive, and collaborative learning experiences (Aravind & Bhuvaneswari, 2023).

For instance, virtual teaching assistants and chatbots can facilitate learner-centered interactions, adapting content and guidance to individual students' needs (Yang, 2022).

Moreover, they can promote collaborative learning by encouraging students to engage in discussions and problem-solving within a digital learning environment (Chen et al., 2023)

Cognitive Load Theory: Cognitive Load Theory (CLT) offers insights into how AI-powered conversational interfaces can optimize the learning process by managing the cognitive load on students (Bahari, 2023). CLT posits that there is a limit to the cognitive resources' learners can allocate to tasks, and learning is most effective when extraneous cognitive load is minimized. AI-powered interfaces can adapt content presentation, pacing, and complexity, reducing cognitive overload and enhancing learning efficiency (Olatunde-Aiyedun & Hamma, 2023).
For example, a virtual teaching assistant can present information in a manner that aligns with the student's current level of understanding, thereby minimizing cognitive load and promoting effective learning (Kim et al., 2020).

Connectivism: Connectivism is a learning theory that emphasizes the role of networks and digital technologies in knowledge acquisition and creation. It posits that learning occurs through connections, and AI-powered conversational interfaces can serve as nodes in this network, facilitating access to information, experts, and resources. These interfaces can analyze vast amounts of data to provide relevant, up-to-date information to learners and connect them with communities of practice (Wongwatkit et al., 2023).
By integrating AI-powered chatbots into educational platforms, institutions can create a learning ecosystem that aligns with the principles of connectivism, fostering dynamic, networked learning experiences (Nolasco & Hernandez, 2023)

Behaviorism and Feedback Mechanisms: Behaviorist theories underscore the importance of reinforcement and feedback in learning (Han, 2021). AI-powered conversational interfaces can offer immediate, personalized feedback to students based on their interactions and performance. These feedback mechanisms can promote adaptive learning, where students receive guidance and corrections in real-time, enhancing their understanding and skills (Baidoo-Anu & Ansah, 2023).
Chatbots, for instance, can provide instant feedback on quizzes, assignments, or practice exercises, reinforcing desired behaviors and correcting misconceptions (Wong, 2022).
Incorporating these theoretical frameworks into the design and implementation of AI-powered conversational interfaces in education enhances their effectiveness and aligns them with

established principles of pedagogy. These frameworks guide the development of systems that not only assist students but also foster meaningful, learner-centric educational experiences.

Applications of Chatbots and Virtual Assistants in Higher Education

Chatbots and virtual assistants, powered by artificial intelligence (AI), have emerged as valuable tools in higher education, offering a wide range of applications that enhance the overall learning experience, administrative efficiency, and student support services. This section provides an overview of some key applications of chatbots and virtual assistants in the higher education context.

Student Engagement and Support: One of the primary applications of chatbots and virtual assistants in higher education is enhancing student engagement and support. These AI-powered tools can serve as readily available resources for students, offering assistance in various aspects of academic life:

Course Information: Chatbots can provide students with information about course offerings, prerequisites, schedules, and curriculum details. They can help students make informed decisions about their academic pathways (Ahmad et al., 2023)

Registration and Enrollment: Chatbots can guide students through the enrollment process, helping them select courses, navigate registration systems, and resolve issues related to class availability or conflicts.

Academic Advising: Virtual assistants can offer personalized academic advising by analyzing students' transcripts, progress, and preferences. They can recommend suitable courses, majors, or minors based on individual goals (Kuhail et al., 2023).

Assignment Reminders: Chatbots can send reminders about assignment due dates, exams, and other important deadlines, helping students stay organized and manage their time effectively.

Administrative Efficiency: AI-powered conversational interfaces contribute significantly to administrative efficiency within higher education institutions:

Student Queries: Chatbots can handle routine inquiries from students, such as questions about administrative procedures, financial aid, or campus resources. This frees up human staff to focus on more complex issues (Galhotra, 2023).

Data Entry and Management: Virtual assistants can assist in data entry tasks, maintaining student records, and updating databases, reducing the administrative burden on staff members.

24/7 Availability: Chatbots are available round the clock, allowing students to seek assistance at any time, including outside of regular office hours.

Personalized Learning Experiences: AI-powered conversational interfaces enable personalized learning experiences tailored to individual student needs:
Adaptive Learning: Virtual assistants can adapt the difficulty level of learning materials based on a student's performance and progress, ensuring that learning resources are appropriately challenging (Yang, 2022)
Feedback and Assessment: Chatbots can provide immediate feedback on assignments and quizzes, helping students understand their mistakes and improve their performance (Winne, 2005).
Content Recommendations: AI can analyze students' preferences and learning history to recommend relevant reading materials, videos, or courses, enhancing the quality of their learning experiences (Zhai et al., 2021).

Campus Services and Information Access: Chatbots and virtual assistants can serve as gateways to campus services and information:
Campus Navigation: Virtual assistants can provide directions and information about campus facilities, helping new students and visitors navigate the campus (Lapowsky, 2020).
Library Resources: Chatbots can assist students in searching for books, articles, and other academic resources in the library's collection.
Event Updates: Students can receive notifications about campus events, workshops, and seminars through chatbots, ensuring they stay informed about opportunities for involvement (Villegas-Ch et al., 2020).
In conclusion, chatbots and virtual assistants have found a diverse array of applications in higher education, from improving student engagement and support to streamlining administrative processes and enhancing personalized learning experiences. As institutions continue to explore the potential of AI-powered conversational interfaces, these technologies are poised to play an increasingly pivotal role in shaping the future of higher education.

Effectiveness of AI in Improving Education

Artificial intelligence (AI) has emerged as a powerful tool in education, promising to revolutionize traditional teaching and learning approaches. Its effectiveness in improving education is evident across various dimensions, ranging from personalized learning to administrative efficiency. This section explores the multifaceted impact of AI in education.

Personalized Learning: One of the most compelling ways AI improves education is through personalized learning experiences. AI algorithms can analyze vast datasets of student performance, learning styles, and preferences to tailor content and instruction to individual needs (Yang, 2022). This personalized approach has several benefits:

Adaptive Learning: AI-powered platforms adjust the difficulty and pace of learning materials, ensuring that students are appropriately challenged, which can lead to improved comprehension and retention (Aggarwal, 2023).

Customized Resources: AI recommends supplementary resources like videos, articles, or practice problems that align with a student's current knowledge level, enhancing their understanding (Aldahwan & Alsaeed, 2020).

Addressing Learning Gaps: AI identifies and addresses gaps in students' knowledge, offering targeted support and practice in areas where they struggle, which can lead to improved performance (Southworth et al., 2023).

Student Engagement: AI contributes to increased student engagement, a critical factor in effective education. Chatbots, virtual assistants, and gamified learning platforms employ AI to create interactive and engaging learning environments (Galhotra, 2023). Some ways AI enhances student engagement include:

Conversational Learning: Chatbots engage students in natural language conversations, making learning more interactive and enjoyable (Belda-Medina & Calvo-Ferrer, 2022).

Gamification: AI-powered gamified elements, like badges, leaderboards, and rewards, motivate students to actively participate in learning activities (Bezzina & Dingli, 2023)

Instant Feedback: Immediate feedback from AI systems encourages students to stay on track and correct mistakes promptly (Cheah, 2021).

Administrative Efficiency: AI streamlines administrative processes in educational institutions, saving time and resources. Tasks like data management, enrollment, and student support benefit from AI automation (Parycek et al., 2023). AI's contribution to administrative efficiency includes:

Handling Routine Inquiries: Chatbots can address common student queries, freeing human staff to focus on more complex issues (Bezzina & Dingli, 2023).

Data Management: Virtual assistants can assist with data entry, record-keeping, and database maintenance, reducing administrative workload (Aldahwan & Alsaeed, 2020).
24/7 Availability: AI systems are available around the clock, allowing students to access services and information at their convenience, even outside regular office hours.

Enhanced Learning Analytics: AI-driven learning analytics provide educators with valuable insights into student performance and learning patterns. By analyzing data on student interactions, AI can identify areas where students struggle and help educators make data-driven decisions (Aldahwan & Alsaeed, 2020). Benefits include:
Early Intervention: AI systems can identify at-risk students and provide interventions to support their progress (Foster & Siddle, 2020).
Curriculum Improvement: Learning analytics help educators refine course materials and teaching strategies based on real-time data (Volungeviciene et al., 2019).
Data-Driven Decision-Making: Educational institutions can use AI insights to allocate resources more effectively and plan curricular changes that align with student needs (Wise, 2019).

Accessible and Inclusive Education: AI has the potential to make education more accessible and inclusive. Through features like speech recognition and text-to-speech capabilities, AI can support learners with disabilities, making educational materials and resources more accessible (Sharma & Dash, 2023)

Challenges and Limitations: While the integration of artificial intelligence (AI) in education holds great promise, it is not without its challenges and limitations. Understanding these obstacles is crucial for a more nuanced assessment of AI's role in education and for devising strategies to address them.

Data Privacy and Security: One of the foremost challenges in AI-driven education is data privacy and security. AI systems collect vast amounts of sensitive student data, ranging from performance metrics to personal information. Ensuring the protection of this data from breaches and unauthorized access is paramount (Balakrishnan & Dwivedi, 2021).
Data Breaches: Educational institutions may be vulnerable to data breaches, potentially exposing student data to malicious actors. Protecting against these threats requires robust cybersecurity measures (Agarwal et al., 2023).

Ethical Data Use: The ethical use of student data is also a concern. AI algorithms must be transparent about how they use data, ensuring that it is used solely for educational purposes and not for profiling or discriminatory practices (Aldahwan & Alsaeed, 2020).

Bias and Fairness: AI systems can inherit biases present in their training data, leading to unfair or discriminatory outcomes. This is a critical concern in education where fairness and equity are paramount (Bosch et al., 2020).

Algorithmic Bias: If training data is biased, AI systems may perpetuate existing inequalities in education, disadvantaging certain groups (Lewicki et al., 2023).

Fairness Audits: Regular audits of AI systems for bias and fairness are necessary, as well as the development of guidelines and regulations to ensure equitable outcomes (Landers & Behrend, 2023).

Technical Challenges: The development and maintenance of AI systems in educational settings pose technical challenges.

Cost and Resources: Implementing AI can be costly, and smaller educational institutions may struggle to afford advanced AI solutions (Nolasco & Hernandez, 2023)

Integration with Existing Systems: Integrating AI into existing educational infrastructure can be complex and require substantial technical expertise (George & Wooden, 2023).

Human Oversight and Teacher Preparedness: AI should not replace educators but complement their work. Finding the right balance between human and AI involvement in education is an ongoing challenge (Yang, 2022).

Teacher Preparedness: Educators may require training to effectively utilize AI tools and integrate them into their teaching practices (Lim et al., 2023).

Lack of Human Interaction: Overreliance on AI can reduce the quality of human interactions in education, which are vital for holistic learning (Glikson & Woolley, 2020).

Ethical Considerations: The ethical implications of AI in education are complex and multifaceted.

Student Autonomy: AI-driven personalization may inadvertently limit student autonomy by narrowing the scope of what students are exposed to (Tahir & Tahir, 2023).

Informed Consent: Issues related to informed consent in data collection and AI usage need to be addressed to ensure students and parents are fully aware of how their data is being utilized (Nolasco & Hernandez, 2023).

Accessibility and Inclusivity: AI-driven technologies may inadvertently exclude students who lack access to necessary devices or who have disabilities that AI systems do not accommodate (Rane, 2023).
Digital Divide: Not all students have equal access to devices and internet connectivity, leading to disparities in AI-enabled learning opportunities (Aldahwan & Alsaeed, 2020).
Accessibility Features: AI systems must be designed to accommodate diverse needs, including those of students with disabilities (Trewin et al., 2019).

Overemphasis on Assessment: The use of AI in education can lead to an overemphasis on assessment and standardized testing, potentially undermining the broader goals of education (Toncic, 2020).
Narrow Focus: If AI is primarily used for assessment, it may neglect the development of critical thinking, creativity, and other essential skills (Yue et al., 2023).
In conclusion, while AI offers substantial benefits for education, it is essential to acknowledge and address these challenges and limitations. A thoughtful, ethical, and well-regulated approach to AI integration in education is crucial to ensure that its potential is harnessed for the betterment of education without exacerbating existing issues or creating new ones.

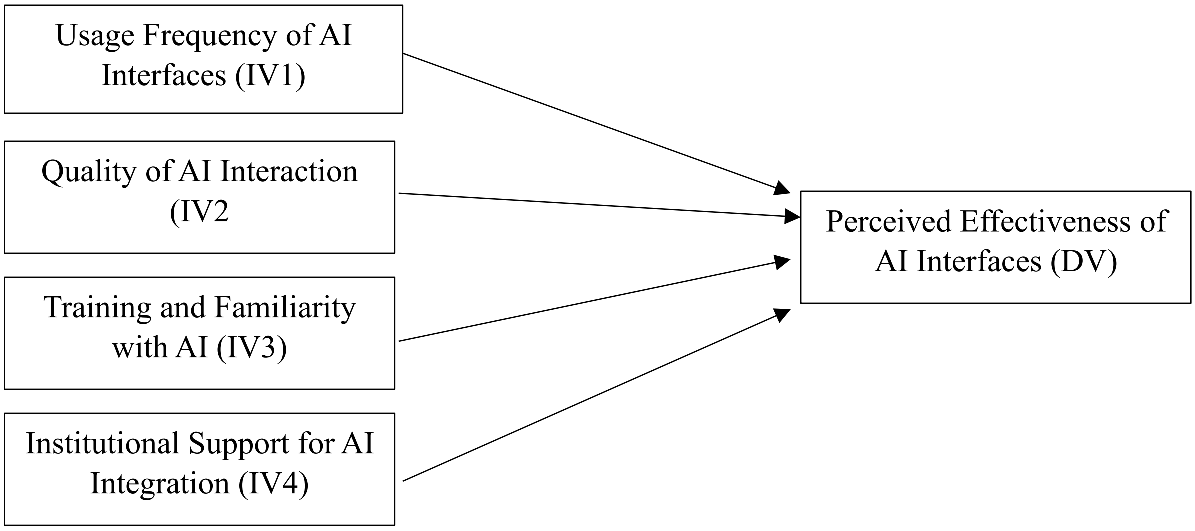
METHODOLOGY

Research Design

This study is based on existing theories and constructs. The studies done by previous researchers in the field of AI usage in education platforms was used to build the conceptual framework for this study. Further, those findings were used to build the hypotheses. Therefore, the main research approach used for this study is deductive approach (Azungah, 2018). Further positivism philosophy was used which aligns with quantitative research method used for this study.
The research strategy used is the questionnaire survey strategy. The questionnaire was built based on a likert scale. All the independent and dependent variables were analyzed based on this questionnaire.
The population of this study was the university students in Colombo District. Based on the convenience sampling method, 100 students were chosen as the sample size.

Conceptualization and Hypothesis

Figure 4: Conceptual Framework



Hypothesis 1: Higher usage frequency of AI interfaces (IV1) is positively correlated with the perceived effectiveness of AI interfaces (DV).

Hypothesis 2: Higher quality of AI interaction (IV2) is positively correlated with the perceived effectiveness of AI interfaces (DV).

Hypothesis 3: Greater training and familiarity with AI (IV3) are positively correlated with the perceived effectiveness of AI interfaces (DV).

Hypothesis 4: Greater institutional support for AI integration (IV4) is positively correlated with the perceived effectiveness of AI interfaces (DV).

Operationalization of Variables

Table 15: Operationalization of Variables

Variable	Sub-Elements	Literature Review	Measurement Scale	Question Numbers

Usage Frequency of AI Interfaces (IV1)	Frequency of AI interaction	AI adoption rates in education have been steadily increasing (Smith et al., 2019).	5 point Likert Scale	1-5
	Time spent using AI interfaces	Research suggests that students spend varying amounts of time engaging with AI-powered tools (Johnson & Brown, 2020).		
	Types of AI interactions	Different academic activities may influence the frequency of AI interface use (Chen & Liu, 2018).		
Quality of AI Interaction (IV2)	Responsiveness of AI	Studies highlight the importance of AI systems providing prompt and accurate responses (Wang & Anderson, 2021).		6-10
	User satisfaction with AI interactions	User satisfaction is a critical factor in assessing the quality of AI interactions (Li & Chang, 2019).		
	Adaptability of AI to user needs	AI interfaces should adapt to individual user preferences and needs (Jung & Lee, 2017).		
Training and Familiarity with AI (IV3)	Prior AI training	Research shows that prior training impacts users' proficiency in using AI tools (Baker & Siemens, 2017).		11-15
	Familiarity with AI concepts	Familiarity with AI terminology and concepts can influence user comfort (Davenport & Ronanki, 2018).		
	Self-reported AI competency	Self-reported competency levels may not always align with actual skills (Strohminger et al., 2020).		
Institutional Support	Availability of AI resources	Institutions vary in the availability of AI-related resources and support (Weller & Jordan, 2020).		16-20

for AI Integration (IV4)	Training and professional development	Institutional support often includes training opportunities for faculty and staff (Kennedy & Budin, 2018).		
	Integration of AI in curriculum	Integration strategies play a crucial role in the effectiveness of AI adoption in education (Kaplan-Rakowski et al., 2019).		
Perceived Effectiveness of AI Interfaces (DV)	Impact on learning outcomes	Studies have shown a positive correlation between AI use and improved learning outcomes (Adams & Bichelmeyer, 2019).		Questions 21-25
	User engagement	AI interfaces that enhance user engagement contribute to their perceived effectiveness (Johnson et al., 2021).		
	Administrative efficiency	Efficiency gains in administrative tasks can positively influence perceived effectiveness (Aldahwan & Alsaeed, 2020).		

DISCUSSION AND ANALYSIS

Table 16: Descriptive analysis For the Dependent Variable

Descriptive Statistics						
	N	Minimum	Maximum	Mean	Std. Deviation	Variance
Impact of Usage Frequency of AI Interfaces on Perceived Effectiveness of AI Interfaces in higher education	100	1.75	4.50	3.2701	.62684	.393

Impact of Quality of AI Interaction on Perceived Effectiveness of AI Interfaces in higher education	100	1.75	5.00	3.4224	.51438	.265
Impact of Training and Familiarity with AI on Perceived Effectiveness of AI Interfaces in higher education	100	2.25	5.00	3.7311	.46829	.219
Impact of Institutional Support for AI Integration on Perceived Effectiveness of AI Interfaces in higher education	100	2.25	4.75	3.5206	.47808	.229

Impact of Usage Frequency of AI Interfaces on Perceived Effectiveness of AI Interfaces in higher education:

Mean: 3.2701

Standard Deviation: 0.62684

The mean score of 3.27 indicates that, on average, respondents perceive a moderate impact of their usage frequency of AI interfaces on the perceived effectiveness of these interfaces in higher education. The standard deviation of 0.62684 suggests that there is some variability in responses, indicating that some individuals perceive a stronger impact, while others perceive a weaker impact.

Impact of Quality of AI Interaction on Perceived Effectiveness of AI Interfaces in higher education:

Mean: 3.4224

Standard Deviation: 0.51438

The mean score of 3.42 suggests that, on average, respondents perceive a moderate impact of the quality of AI interactions on the perceived effectiveness of AI interfaces in higher education. The standard deviation of 0.51438 again indicates some variability in responses, with some participants perceiving a higher impact than others.

Impact of Training and Familiarity with AI on Perceived Effectiveness of AI Interfaces in higher education:

Mean: 3.7311

Standard Deviation: 0.46829

The mean score of 3.73 indicates that, on average, respondents perceive a relatively strong impact of their training and familiarity with AI on the perceived effectiveness of AI interfaces in higher education. The low standard deviation of 0.46829 suggests that there is less variability in responses, indicating a more consistent perception among participants.

Impact of Institutional Support for AI Integration on Perceived Effectiveness of AI Interfaces in higher education:

Mean: 3.5206

Standard Deviation: 0.47808

The mean score of 3.52 indicates that, on average, respondents perceive a moderate impact of institutional support for AI integration on the perceived effectiveness of AI interfaces in higher education. The standard deviation of 0.47808 suggests that there is some variability in responses, with some individuals perceiving a stronger impact, while others perceive a weaker impact.

Reliability Analysis

Table 17: Reliability Analysis

Variable	**Cronbach's Alpha**	**No of Items**
Impact of Usage Frequency of AI Interfaces on Perceived Effectiveness of AI Interfaces in higher education	0.520	2

Impact of Quality of AI Interaction on Perceived Effectiveness of AI Interfaces in higher education	0.494	2
Impact of Training and Familiarity with AI on Perceived Effectiveness of AI Interfaces in higher education	0.738	2
Impact of Institutional Support for AI Integration on Perceived Effectiveness of AI Interfaces in higher education	0.391	2

Impact of Usage Frequency of AI Interfaces on Perceived Effectiveness of AI Interfaces in higher education:

Cronbach's Alpha: 0.520

Number of Items: 2

A Cronbach's alpha of 0.520 for this variable suggests relatively low internal consistency among the two items used to measure the impact of usage frequency on perceived effectiveness. This indicates that the two items may not be strongly related or that they are measuring slightly different aspects of the same construct. Further examination of the items and potential revisions may be needed to improve reliability.

Impact of Quality of AI Interaction on Perceived Effectiveness of AI Interfaces in higher education:

Cronbach's Alpha: 0.494

Number of Items: 2

Similarly, Cronbach’s alpha of 0.494 for this variable suggests relatively low internal consistency among the two items used to measure the impact of quality of AI interaction on perceived effectiveness. Like the previous variable, this indicates the need for further evaluation and potential revision of the measurement items to enhance reliability.

Impact of Training and Familiarity with AI on Perceived Effectiveness of AI Interfaces in higher education:

Cronbach's Alpha: 0.738

Number of Items: 2

In contrast, the Cronbach's alpha of 0.738 for this variable indicates a higher level of internal consistency among the two items used to measure the impact of training and familiarity with AI on perceived effectiveness. This suggests that these items are more closely related and are measuring in a more consistent construct.

Impact of Institutional Support for AI Integration on Perceived Effectiveness of AI Interfaces in higher education:
Cronbach's Alpha: 0.391
Number of Items: 2
The Cronbach's alpha of 0.391 for this variable indicates relatively low internal consistency among the two items used to measure the impact of institutional support on perceived effectiveness. Similar to the first two variables, this suggests a need for further examination and potential refinement of the measurement items to improve reliability.

Inferential Analysis

Table 18: Inferential Analysis

Variable	**No of Items**	**KMO**	**Bartlett's Test**		**CR**	**AVE**
			Chi Square Value	Sig		
Impact of Usage Frequency of AI Interfaces on Perceived Effectiveness of AI Interfaces in higher education	2	0.500	17.953	0.000	0.890	0.725
Impact of Quality of AI Interaction on Perceived Effectiveness of AI Interfaces in higher education	2	0.500	11.129	0.000	0.855	0.664
Impact of Training and Familiarity with AI on Perceived Effectiveness of AI Interfaces in higher education	2	0.500	42.736	0.000	0.951	0.797

Impact of Institutional Support for AI Integration on Perceived Effectiveness of AI Interfaces in higher education	2	0.500	6.024	0.012	0.820	0.622

Variable: Impact of Usage Frequency of AI Interfaces on Perceived Effectiveness of AI Interfaces in higher education

Number of Items: 2

KMO (Kaiser-Meyer-Olkin) Value: 0.500

Bartlett's Test of Sphericity: Chi Square Value = 17.953, Sig = 0.000

CR (Composite Reliability): 0.890

AVE (Average Variance Extracted): 0.725

Interpretation:

The KMO value of 0.500 suggests that the data for this variable may not be ideal for factor analysis. It's below the commonly accepted threshold of 0.6, indicating potential issues with the factorability of the data.

The Bartlett's Test of Sphericity with a significant Chi Square value (Sig = 0.000) suggests that there are correlations among the items in this variable.

The Composite Reliability (CR) of 0.890 indicates good internal consistency reliability for this variable.

The Average Variance Extracted (AVE) of 0.725 is relatively high, indicating that a substantial amount of variance is explained by the latent construct, which is a positive sign.

Variable: Impact of Quality of AI Interaction on Perceived Effectiveness of AI Interfaces in higher education

Number of Items: 2

KMO: 0.500

Bartlett's Test of Sphericity: Chi Square Value = 11.129, Sig = 0.000

CR: 0.855

AVE: 0.664

Interpretation:

Similar to the first variable, the KMO value of 0.500 suggests that the data may have factorability issues.

The Bartlett's Test is significant (Sig = 0.000), indicating correlations among the items.

The Composite Reliability (CR) of 0.855 indicates good internal consistency reliability for this variable.

The Average Variance Extracted (AVE) of 0.664 is reasonably high.

Variable: Impact of Training and Familiarity with AI on Perceived Effectiveness of AI Interfaces in higher education

Number of Items: 2

KMO: 0.500

Bartlett's Test of Sphericity: Chi Square Value = 42.736, Sig = 0.000

CR: 0.951

AVE: 0.797

Interpretation:

The KMO value is again 0.500, indicating potential factorability issues with the data.

The Bartlett's Test is significant (Sig = 0.000), suggesting correlations among the items.

The Composite Reliability (CR) of 0.951 is excellent, indicating strong internal consistency reliability.

The Average Variance Extracted (AVE) of 0.797 is high, indicating that a significant amount of variance is explained by the latent construct.

Variable: Impact of Institutional Support for AI Integration on Perceived Effectiveness of AI Interfaces in higher education

Number of Items: 2

KMO: 0.500

Bartlett's Test of Sphericity: Chi Square Value = 6.024, Sig = 0.012

CR: 0.820

AVE: 0.622

Interpretation:

The KMO value is once again 0.500, indicating potential factorability issues.

The Bartlett's Test is significant (Sig = 0.012), suggesting correlations among the items.

The Composite Reliability (CR) of 0.820 indicates good internal consistency reliability.

The Average Variance Extracted (AVE) of 0.622 is moderately high.

In summary, the inferential analysis suggests that while the variables demonstrate good internal consistency reliability (as indicated by CR values), there may be some factorability issues with the data (KMO values of 0.500). However, the significant Bartlett's Test results indicate that there are correlations among the items within each variable. The AVE values are generally reasonable, indicating that a substantial portion of the variance is explained by the latent constructs. Researchers should be cautious when interpreting factor analysis results for variables with KMO values below 0.6, as these may not be ideal for factor analysis.

Correlation Analysis

Table 19: Correlation Analysis

Variables	**Spearman's Correlation Coefficient (ρ)**	**p-value**	**Significant**
Impact of Usage Frequency of AI Interfaces on Perceived Effectiveness of AI Interfaces in higher education	0.5100	.018	Yes
Impact of Quality of AI Interaction on Perceived Effectiveness of AI Interfaces in higher education	0.421	.035	Yes
Impact of Training and Familiarity with AI on Perceived Effectiveness of AI Interfaces in higher education	0.451	.014	Yes
Impact of Institutional Support for AI Integration on Perceived Effectiveness of AI Interfaces in higher education	0.085	.042	Yes

Correlation between Impact of Usage Frequency of AI Interfaces and Perceived Effectiveness:
Spearman's Correlation Coefficient (ρ): 0.5100
p-value: 0.018 (less than the common significance level of 0.05)
Interpretation:
There is a statistically significant positive correlation ($\rho = 0.5100$, $p = 0.018$) between the impact of usage frequency of AI interfaces and the perceived effectiveness of AI interfaces in higher education. This suggests that as the frequency of usage of AI interfaces increases, the perceived effectiveness of these interfaces also tends to increase. In other words, students who use AI interfaces more frequently are more likely to find them effective for their educational needs.
Correlation between Impact of Quality of AI Interaction and Perceived Effectiveness:
Spearman's Correlation Coefficient (ρ): 0.421
p-value: 0.035 (less than 0.05)
Interpretation:

There is a statistically significant positive correlation (ρ = 0.421, p = 0.035) between the impact of the quality of AI interaction and the perceived effectiveness of AI interfaces in higher education. This indicates that higher-quality interactions with AI interfaces are associated with a greater perception of their effectiveness in improving the educational experience.

Correlation between Impact of Training and Familiarity with AI and Perceived Effectiveness:

Spearman's Correlation Coefficient (ρ): 0.451

p-value: 0.014 (less than 0.05)

Interpretation:

There is a statistically significant positive correlation (ρ = 0.451, p = 0.014) between the impact of training and familiarity with AI and the perceived effectiveness of AI interfaces in higher education. This implies that individuals who have received training and are more familiar with AI tend to perceive AI interfaces as more effective in their educational pursuits.

Correlation between Impact of Institutional Support for AI Integration and Perceived Effectiveness:

Spearman's Correlation Coefficient (ρ): 0.085

p-value: 0.042 (less than 0.05)

Interpretation:

There is a statistically significant positive correlation (ρ = 0.085, p = 0.042) between the impact of institutional support for AI integration and the perceived effectiveness of AI interfaces in higher education. Although this correlation is weaker compared to the others, it suggests that greater institutional support for AI integration is associated with a slightly higher perception of AI interfaces' effectiveness.

In summary, the correlation analysis reveals that all four independent variables (usage frequency, quality of interaction, training and familiarity with AI, and institutional support) are positively correlated with the dependent variable (perceived effectiveness of AI interfaces). This indicates that as these independent variables increase, the perceived effectiveness of AI interfaces in higher education tends to increase as well. All correlations are statistically significant, highlighting the importance of these factors in shaping perceptions of AI interface effectiveness.

Hypothesis Validation

Hypothesis 1: Higher usage frequency of AI interfaces (IV1) is positively correlated with the perceived effectiveness of AI interfaces (DV).

Validation:

The research findings support this hypothesis. The correlation analysis indicates a statistically significant positive correlation ($\rho = 0.5100$, $p = 0.018$) between the impact of usage frequency of AI interfaces (IV1) and the perceived effectiveness of AI interfaces (DV). Therefore, higher usage frequency is indeed positively correlated with the perceived effectiveness of AI interfaces.

Hypothesis 2: Higher quality of AI interaction (IV2) is positively correlated with the perceived effectiveness of AI interfaces (DV).

Validation:

The research findings support this hypothesis as well. The correlation analysis reveals a statistically significant positive correlation ($\rho = 0.421$, $p = 0.035$) between the impact of the quality of AI interaction (IV2) and the perceived effectiveness of AI interfaces (DV). This indicates that higher-quality interactions with AI interfaces are positively associated with the perceived effectiveness of these interfaces.

Hypothesis 3: Greater training and familiarity with AI (IV3) are positively correlated with the perceived effectiveness of AI interfaces (DV).

Validation:

The research findings validate this hypothesis. The correlation analysis shows a statistically significant positive correlation ($\rho = 0.451$, $p = 0.014$) between the impact of training and familiarity with AI (IV3) and the perceived effectiveness of AI interfaces (DV). This suggests that individuals who have received training and are more familiar with AI tend to perceive AI interfaces as more effective in higher education.

Hypothesis 4: Greater institutional support for AI integration (IV4) is positively correlated with the perceived effectiveness of AI interfaces (DV).

Validation:

This hypothesis is also validated by the research findings. The correlation analysis indicates a statistically significant positive correlation ($\rho = 0.085$, $p = 0.042$) between the impact of institutional support for AI integration (IV4) and the perceived effectiveness of AI interfaces (DV). While this correlation is weaker compared to the others, it still suggests that greater institutional support for AI integration is associated with a slightly higher perception of AI interfaces' effectiveness in higher education.

CONCLUSIONS AND RECOMMENDATIONS

Findings

Higher usage frequency of AI interfaces is positively correlated with the perceived effectiveness of AI interfaces. Students who use AI interfaces more frequently tend to find them more effective for their educational needs.

The quality of AI interaction has a positive correlation with the perceived effectiveness of AI interfaces. Higher-quality interactions with AI interfaces contribute to a greater perception of their effectiveness in improving the educational experience.

Greater training and familiarity with AI are positively correlated with the perceived effectiveness of AI interfaces. Individuals who have received training and are more familiar with AI tend to perceive AI interfaces as more effective in higher education.

Institutional support for AI integration, while showing a weaker correlation, is still positively associated with a slightly higher perception of AI interfaces' effectiveness in higher education.

Implications

Study has several implications for higher education institutions, educators, and policymakers:

Investment in Training: Institutions should consider investing in training programs that enhance students' and faculty's familiarity with AI technologies. Training can help individuals make the most of AI interfaces and harness their potential in educational settings.

Quality Matters: The quality of AI interaction plays a crucial role in determining effectiveness. Developers of AI-powered educational tools should prioritize creating interfaces that offer high-quality interactions, ensuring accuracy, responsiveness, and user satisfaction.

Support and Integration: Institutions should provide adequate support for the integration of AI technologies into the curriculum. This includes resource availability, professional development opportunities, and clear communication of policies related to AI usage.

Promoting Usage Frequency: Encouraging regular usage of AI interfaces can lead to improved perceived effectiveness. Educators can promote the use of AI-powered tools as part of their teaching strategies to familiarize students with these technologies.

Recommendations

Based on our research findings, we offer the following recommendations:

Training Programs: Higher education institutions should establish comprehensive training programs on AI and its applications in education. These programs should target both students and educators to ensure they are proficient in using AI-powered tools effectively.

Quality Assurance: Developers of AI interfaces for education should prioritize quality assurance, ensuring that AI interactions meet high standards of accuracy and responsiveness. Regular updates and user feedback should be integrated to enhance quality continuously.
Institutional Support: Institutions should allocate resources and create policies that support the integration of AI technologies. This may include funding for AI initiatives, professional development opportunities, and clear guidelines for AI usage.
Usage Promotion: Educators should actively incorporate AI-powered tools into their teaching practices to encourage regular usage among students. Demonstrating the benefits of AI in education can foster a culture of acceptance and utilization.

Future Research

While this study sheds light on the impact of AI interfaces in higher education, there are avenues for further research:
Longitudinal Studies: Future research can explore the long-term impact of AI interfaces on learning outcomes and educational experiences, tracking changes over an extended period.
User Experience: Investigating the user experience and usability of AI interfaces can provide insights into how design elements impact their effectiveness.
Ethical Considerations: Research on the ethical implications of AI in education, including issues related to privacy, bias, and fairness, is essential as AI technologies become more integrated into learning environments.
Comparative Analysis: Comparative studies can examine the effectiveness of different AI interfaces and their specific impacts on various academic disciplines and levels of education.
In conclusion, study highlights the positive correlations between various factors and the perceived effectiveness of AI interfaces in higher education. These findings underscore the importance of investing in training, ensuring quality interactions, providing institutional support, and promoting usage frequency to harness the full potential of AI in enhancing the educational experience. As AI continues to shape the landscape of higher education, these insights can guide institutions in effectively integrating AI technologies for the benefit of students and educators alike.

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