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Unlocking the Potential of Large Language Models in Education: Factors Influencing Adoption by Instructional Designers and Academics

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Abstract

Aim/Purpose	The study investigates the factors influencing the acceptance and utilisation of large language models (LLMs) (predictor variables of LLM usage), such as ChatGPT, in Learning design by instructional designers and university-teaching academics from various countries.
Background	Large language models (LLMs) have exploded onto the scene, transforming the landscape of learning design. Instructional designers and university teaching academics have been overburdened with content creation for their teaching programmes, and the arrival of LLM models will help in this regard by developing more interactive content that drives student engagement and, in turn, contributes to student success. Since LLMs are a relatively new phenomenon, little is known about the factors influencing their acceptance in learning design; therefore, this research is needed, as learning design principles are the bedrock of student engagement and success.
Methodology	A cross-sectional correlational quantitative study was employed. Data was collected using an online questionnaire posted on social media, including LinkedIn, from 203 instructional designers and university teaching academics. Purposive and snowball sampling methods were used to target instructional designers and

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university teaching academics at colleges and universities worldwide. Participants were asked to share the survey link with fellow instructional designers and university-teaching academics in their communities. The factor structure of the data was determined using exploratory factor analysis. Nonetheless, the factor structure derived from the LLMs did not entirely reflect the original configuration of the Unified Theory of Acceptance and Use of Technology (UTAUT3), as certain predictors appeared to coalesce, indicating LLMs' unique nature in learning design. Confirmatory factor analysis was used to verify the fit of the data on the measurement model. First-order and second-order structural modelling were used to identify the structural relationships among the variables.

Contribution: The study determines significant factors for the acceptance of LLMs by instructional designers and academic teaching staff in learning design, enabling possible opportunities for best practices in the field through interventions to optimize LLM usage. The study applies the technology acceptance model to the emerging LLM technology and extends the technology acceptance model by adding the trust construct as a predictor variable.

Findings: The structural analysis results indicated that the ingrained LLM practices, LLM peer-driven expectations, innovative propensity towards LLM adoption, reliability and provider trust in LLMs, and ease of use and support influenced perceived LLM benefits and usage, but community standards and infrastructure had no influence. The second-order structural equation modelling indicated that perceived LLM benefits and usage and ingrained LLM habits contributed most to the learning design.

Recommendations for Practitioners: Teaching academics and instructional designers must use LLMs in designing content, assessments, and interactive learning activities, and attend LLM training workshops on prompting and best practices in integrating LLMs into learning and teaching to see their benefits; hence, regular use of LLMs will then lead to trust and innovation in LLMs usage, enhancing learning design and improving student learning outcomes.

Recommendations for Researchers: Researchers must use mixed methods approaches to have a deeper understanding of the factors influencing LLMs. Since habit and perceived LLM benefits and usage contributed the most variance to learning design, researchers must investigate strategies that optimise these factors in learning design, such as effective intervention strategies that can help form positive LLM habits. In addition, the findings provide researchers with a starting point for future research. Further researchers must investigate interventions that optimise the influence of personal innovativeness and trust that contributed the least variance to learning design, hence unlocking the potential of LLMs in learning design through innovation, responsible, and ethical use.

Impact on Society: The use of LLMs in learning design has a high possibility of transforming education, specifically the learning design landscape. Using LLMs will free up more time for teaching academics and instructional designers so that they spend more time on higher-order thinking skill demands. Consequently, the students will be exposed to more engaging and interactive content, resulting in improved learning outcomes.

Future Research: Future research must include context-derived external variables in technology acceptance models, such as levels of prompting competencies, to provide a deeper understanding of LLMs. In addition, future research must be based on the application and impact of LLMs on student engagement and success, and their attainment of 21st-century skills.

Keywords artificial intelligence, large language models, instructional design, teaching academics, learning design, habit, social influence

INTRODUCTION

Recently, Artificial intelligence (AI), specifically large language models (LLMs), such as ChatGPT (Generative Pretrained Transformer), have taken the world by storm (Elkins et al., 2023; García-Méndez et al., 2025; Köpf et al., 2023; Lanzi & Loiacono, 2023; Pan et al., 2023). The emergence of these language models (LLMs) has created many learning design opportunities (Yang & Stefaniak, 2025), particularly for instructional designers and university teaching academics(instructors) involved in content development for teaching and learning in higher education. Instructional designers work with subject matter experts (SMEs), usually academic teaching staff, to develop learning processes and align them with best pedagogical practices (Pollard & Kumar, 2022). Learning design is a framework that captures a learning event's teaching and learning processes (Koper, 2005, 2006), where good learning designs lead to student engagement and academic gains (Nguyen et al., 2018).

LLMs are revolutionising how instructional designers design and instructors develop and deliver instructional content (Baytak, 2023; de Fine Licht, 2023; Greene-Harper, 2023; Meyer et al., 2023). For instance, LLMs can be efficiently used to create authentic learning materials such as learning objectives, quizzes, videos, rubrics, assessments, and course outlines (Gibson, 2023; Harvey et al., 2025; Kasneci et al., 2023; Kereselidze, 2023; Meyer et al., 2023; Stone, 2023; Veletsianos, 2023). LLMs generate high-quality content and thus decrease the cognitive load when creating questions (Elkins et al., 2023). However, teaching academics expressed concerns about imprecise citations and sources(inaccurate) (Hennekeuser et al., 2025). In addition, LLMs save time or lessen the workloads in content preparation (Bissessar, 2023; Bonner et al., 2023; Elkins et al., 2023; Sağın et al., 2024; Sridhar et al., 2023; Yadav, 2023). The freeing of time means that instructional designers or instructors can now concentrate on designing high-order thinking activities (Beale, 2025; Bolick & Da Silva, 2024; Gibson, 2023).

While LLMs hold immense potential for creating accurate content for teaching and learning, they have challenges or limitations that may dissuade instructional designers or instructors from using them. These challenges include plagiarism, misinformation, bias, privacy, ethical, and copyright issues that are inherent in LLMs (Abd-alrazaq et al., 2023; Kasneci et al., 2023; Meyer et al., 2023; Niemi et al., 2023; Pan et al., 2023; Sallam, 2023; Woo et al., 2024; Yadav, 2023; Yang & Stefaniak, 2025). Bias concerns about the accuracy and reliability of the generated outputs prevent instructional designers and instructors from extensive use of LLMs (Leiker et al., 2023; Yang & Stefaniak, 2025). Consequently, awareness of these LLM limitations or potential violations may force instructional designers and university teaching academics not to accept and use LLMs (Kasneci et al., 2023; Niemi et al., 2023; Pan et al., 2023). In addition, a lack of technical know-how in using LLMs may deter adoption (Hadi et al., 2023; Long & Magerko, 2020), and the converse holds. For instance, a lack of or limited prompt engineering (programming in natural language) skills, artificial intelligence literacies strategies, and critical thinking skills may lead to unreliable and potentially misleading outputs, further fuelling reliability worries (Bolick & Da Silva, 2024; Chang et al., 2023; Kasneci et al., 2023; Yadav, 2023) leading to instructional designers maintaining a cautious outlook toward LLM reliability (McNeill et al., 2025). Several authors (Eager & Brunton, 2023; Reynolds & McDonell, 2021; Wu et al., 2022; Zamfirescu-Pereira et al., 2023) emphasised the importance of sound, prompt engineering skills as a panacea for generating accurate content. Knowing when to apply a zero-shot (which does not have an example), one-shot prompt (which has one example) or few-shot prompt (which has examples) to improve the accuracy and reliability of content (Elkins et al., 2023; Reynolds & McDonell, 2021; Russe et al., 2024) or a chain prompt where the output of one step becomes the input of the other and then aggregating the outputs of the steps (Wu et al., 2022) or when to use high or lower temperature output (Wu et al., 2022; Yadav, 2023) is important for generating accurate content for complex tasks such as assessments (Eager & Brunton, 2023). A lack of these skills may frustrate instructional designers or instructors when they get inaccurate outputs, compelling them not to use LLMs, and the converse holds (Yadav, 2023). Zamfirescu-Pereira et al. (2023) reported that designing effective prompts is a huge challenge to content output accuracy. The fact that LLMs are somehow inaccurate contributes to instructional designers' and instructors' poor adoption of LLMs. As a result, some instructional designers or instructors may prefer to use peer-reviewed databases such as Google Scholar from the outset. Furthermore, since LLMs are relatively new, some instructional designers are sceptical of their capabilities (Sridhar et al., 2023). High traffic-induced unavailability encountered when using LLMs, such as ChatGPT (Filipec & Woithe, 2023), is another deterrent to LLM adoption.

The successful adoption of LLM will also depend on biographical factors. Draxler et al. (2023) reported that males had a greater and statistically significant difference than females in LLM adoption. In the same study, younger people had a greater and statistically significant effect on LLM usage than older people (Draxler et al., 2023). Hence, understanding the disparities in the influence of biographical factors will help design effective interventions to promote equitable access and benefits to all in LLM usage.

This study investigates the factors influencing the adoption of LLMs by instructional designers and university teaching academics(instructors). This study is important because, as LLMs become prevalent, it is important to understand the factors that drive their acceptance and use in education, paving the way for how they can be optimised for teaching and learning, used responsibly and ethically, thus improving student learning outcomes through increased engagement (S. Wang et al., 2024) while informing policy and practice. Further, understanding the acceptance of LLMs in learning design will pave the way for best practices and guidelines in the field, and a good understanding of the significant factors will help to design LLM-based training and support resources that meet the needs of instructional designers and university academics. Besides, understanding acceptance and use patterns enables continuous improvement in LLM technologies to serve educational needs better. This study will also determine the applicability of the Unified Theory of Acceptance and Use of Technology 3 (UTAUT3) to an emerging technology of artificial intelligence in learning design.

Since LLMs are a relatively new phenomenon, there is a dearth of literature on the acceptance of LLMs in learning design, especially for instructional designers (Luo et al., 2025; Pereira et al., 2024). In addition, Kumar et al. (2024) reported that there is scarce literature on how instructional designers use LLMs in their practices. While descriptive studies on instructional designers' use of large language models (LLMs) are available (e.g., Luo et al., 2025), few investigations have employed established technology adoption frameworks such as UTAUT3, hence limiting the understanding of the factors that drive the use and acceptance of LLMs (McNeill et al., 2025). In addition, few studies have employed a purely quantitative approach to examine instructional designers' use of AI, limiting generalizable insights into adoption patterns and influencing factors (Avedzi, 2025). However, studies on using LLMs for instructors in higher education have mushroomed on the scene (Bhat et al., 2024; Camilleri, 2024; Hennekeuser et al., 2025; Shahzad et al., 2024; Soodan et al., 2024). Because instructional designers serve as institutional change agents and play a pivotal role in leading the adoption of LLMs in teaching and learning, research into their use of LLMs is timely and essential (Bond et al., 2023; Kumar et al., 2024). Accordingly, the research questions that will guide this study are:

- What factors influence instructional designers' and instructors' behavioural intentions and use of LLMs in learning design?
- How do the resultant individual factors contribute to Learning design?
- How do factors like age, gender, and qualification moderate the variables in LLM adoption?

We employed a cross-sectional quantitative study using structural equation modelling to analyse the data to investigate the acceptance of LLMs by instructional designers and teaching academics. This study uses an extended version of the UTAUT3 model, integrating trust in LLM providers and trust in LLMs as additional predictors. Our key findings indicate that the combined influence of ingrained LLM habits and social influence, perceived LLM benefits, and usage (PEBIBU) contributed most to learning design. In contrast, trust in LLM had the least contribution to learning design.

LITERATURE REVIEW

LLMs use natural language processing (NLP), a machine learning strand, to analyse and interpret texts and images (Krupp et al., 2023; Niemi et al., 2023; Pan et al., 2023; Salas-Pilco et al., 2022). Natural language processing (NLP) uses statistical patterns to predict, interpret, and generate text and meaning (Bonner et al., 2023; Pan et al., 2023). LLMs were trained on vast amounts of web data and have emerged as powerful NLPs (Bonner et al., 2023; Kasneci et al., 2023; Liu et al., 2023; Y. Wang et al., 2023).

When used effectively, LLMs foster the development of higher-order thinking skills and creativity, which are desired tools for designing dynamic and engaging learning experiences (Kereselidze, 2023). While LLMs have proved to be effective in content generation and many other tasks (Bonner et al., 2023; Kasneci et al., 2023; Liu et al., 2023; Tam et al., 2023; Y. Wang et al., 2023; Yang & Stefaniak, 2025), they have limitations. For instance, LLMs are prone to hallucinating (generating misleading or false information) if they do not understand complex queries (Chang et al., 2023; Strzelecki, 2023; Tam et al., 2023). The limitations can be primarily attributed to inaccurate or biased training data (Beale, 2025; Kaddour et al., 2023; Leiker et al., 2023; Menon & Shilpa, 2023; Moore et al., 2023; Y. Wang et al., 2023). The LLMs are based on probability prediction of text (Bonner et al., 2023; Pan et al., 2023) and are not 100% accurate and reliable (Yadav, 2023). In addition, LLMs may be using outdated information (Kaddour et al., 2023; Liu et al., 2023).

LLMs also perpetuate and amplify biases present in training data (Beale, 2025; Kasneci et al., 2023; Pan et al., 2023), leading to inaccurate information and unfairness towards other vulnerable groups (Hadi et al., 2023; Kasneci et al., 2023; Pan et al., 2023). Bias concerns about the accuracy and reliability of the generated outputs may curtail LLM usage (Kozan et al., 2025; Leiker et al., 2023). However, with human oversight to mitigate bias, the LLMs can be significantly accurate and reliable (Ayanwale et al., 2022; Hadi et al., 2023; Kasneci et al., 2023; Krupp et al., 2023; Tam et al., 2023; Yadav, 2023). For instance, lowering the temperature of the model (Yadav, 2023), fine-tuning the model (Yadav, 2023), and using proper prompt engineering strategies such as chunking (chain prompting) (Beale, 2025; Malik et al., 2025; Wu et al., 2022) and roleplaying (few-shots prompting) (Eager & Brunton, 2023; Reynolds & McDonell, 2021) mitigate problems of hallucinations (Hadi et al., 2023; Woo et al., 2024).

Before the advent of LLMs, instructional designers and university teaching staff were overburdened with tasks such as gathering and synthesising information and providing timely feedback during module designing and teaching, respectively (Alkafaween et al., 2025; Hennekeuser et al., 2025; He-Yueya et al., 2024; Lee et al., 2024; S. Wang et al., 2024). Further, crafting content to meet the diverse needs of their students was difficult, often leading to content designed for a one-size-fits-all approach with limited personalization or limited scalability (Yadav, 2023), leading to labour-intensive and time-consuming design processes (S. Wang et al., 2024). Likewise, constructive alignment (the alignment of intended learning outcomes, instructional strategies, learning activities, and assessment methods) is time-consuming and labour-intensive (Pereira et al., 2024). For instance, Davis and Lee (2023) reported that instructional designers and university lecturers would take weeks to search for relevant resources on the Internet. However, with LLMs, this exploit can be achieved in no time, but the LLM outputs are not always accurate, hence the necessity of human oversight to ensure the quality of the content (Kozan et al., 2025; Pereira et al., 2024; Yadav, 2023). Now with LLMs, instructional designers and teaching academics can create adaptive content tailored to different students effortlessly (Harvey et al., 2025; S. Wang et al., 2024), resulting in significant time-saving benefits, thereby reducing the workload for instructional designers and teaching academics (Davis & Lee, 2023; Kozan et al., 2025; Schaper, 2024; Yang & Stefaniak, 2025). Furthermore, instructional designers and teaching academics can use LLMs to design interactive teaching resources effortlessly, without requiring specialized skills, thus leveling the learning design field (Bećirović, 2023). While LLMs optimize time spent, for instance, in constructive alignment, some instructional designers and university teaching academics find it challenging to integrate them into their course development due to various reasons that include poor prompting skills (Zamfirescu-Pereira et al., 2023) and the LLMs' propensity to make inaccurate content predictions (Leiker et al., 2023).

THEORETICAL FRAMEWORK

In this study, the Unified Theory of Acceptance and Use of Technology (UTAUT3) was chosen ahead of the other technology acceptance models because it comprises personal innovativeness, which may inspire instructional designers and instructors to experiment with new technologies such as LLMs (Farooq et al., 2017). The UTAUT3 comprises social influence, facilitating conditions, hedonic motivation, habit, personal innovativeness, performance, and effort expectancy. Figure 1 shows the elements of the UTAUT3 framework.

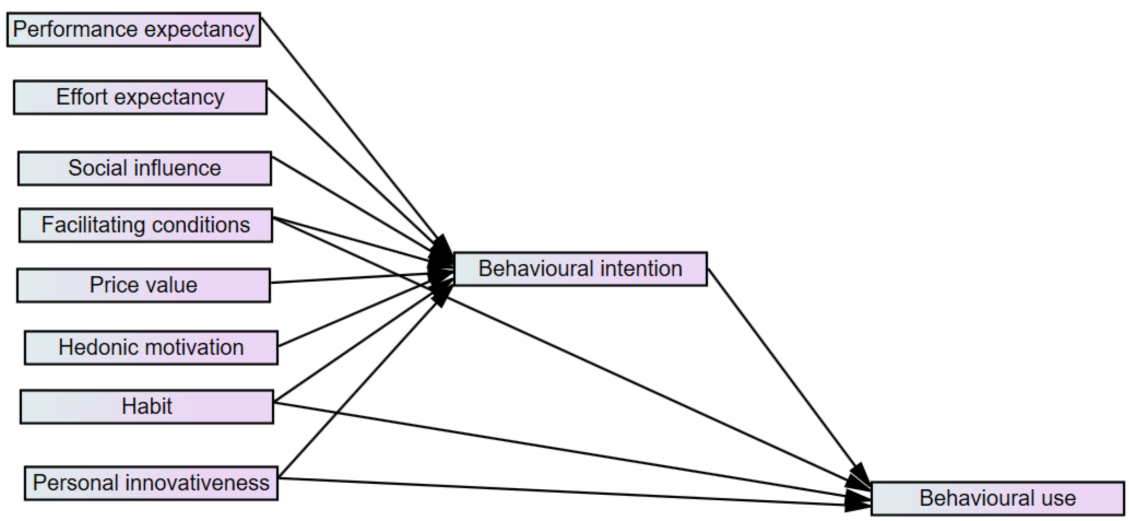

Figure 1. The elements of the UTAUT3 framework (adopted from Farooq et al., 2017)

Performance expectancy is the degree to which an individual believes that using the system will help them attain gains in job performance (Venkatesh et al., 2003). Effort expectancy is the degree of ease associated with using the system. Social influence is the degree to which an individual perceives that important others believe he or she should use the new system. Facilitating conditions are the degree to which an individual believes that an organisation's technical infrastructure exists to support the use of the system. Habit is defined as the extent to which individuals perform behaviours automatically when using a system (Venkatesh et al., 2012). Hedonic motivation is the fun or pleasure of using a technology. Personal innovativeness is the perceived predisposition to the independent use of a system (Farooq et al., 2017). Behavioural intention is the degree to which users intend to use a system. Behavioural use is the extent of the actual usage of a system (Venkatesh et al., 2003). Price value is defined as an individual's trade-off between the perceived benefits of a system and the cost of using the system (Venkatesh et al., 2012).

Proposed Research Model

All the elements of the UTAUT except price value were incorporated into the proposed research model. However, price value was excluded because there are free versions of LLMs that instructional designers or instructors can use. In addition, trust in LLMs (TT) and trust in the LLM providers (TP) were also included in the proposed research model. Trust is when individuals or organisations perceive a technology to be reliable, and when individuals perceive it to be reliable, they are likely to adopt and use it (Ayanwale & Molefi, 2024). Trust in the provider is the extent to which people believe that the provider of a system is trustworthy. Figure 2 shows the proposed research model.

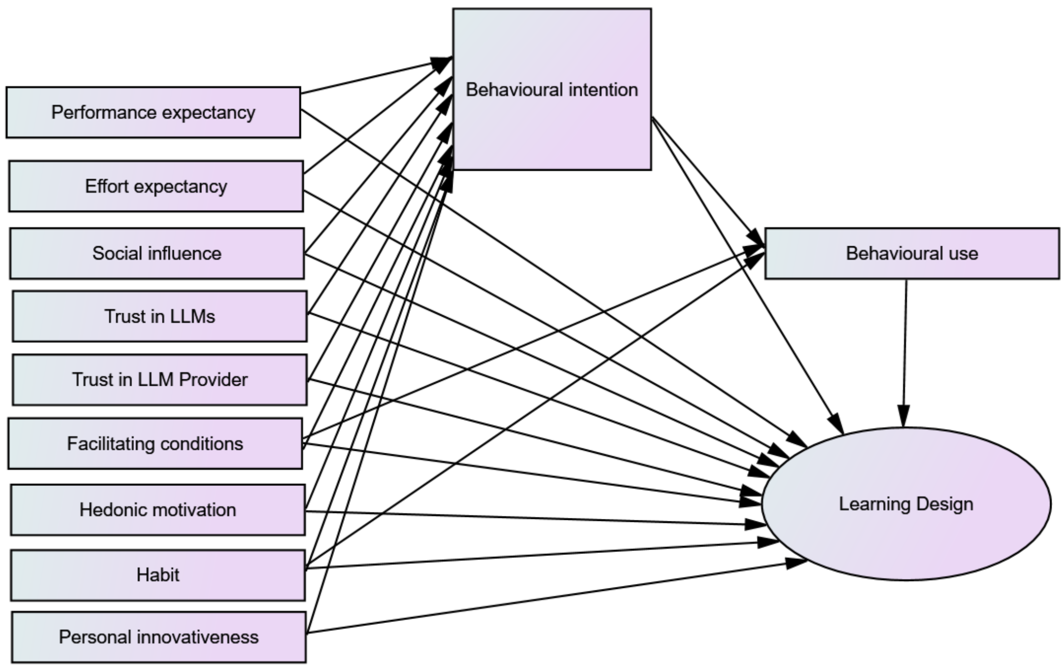

Figure 2. The proposed research model

In the following section, the definitions of the UTAUT3 constructs were operationalised. However, hypotheses were not included at this stage. This is because LLMs are new, and their factor structure, as predicted by the UTAUT3, may differ; hence, hypotheses will be drawn out once the factor structure has been determined through exploratory factor analysis, which was done in the later sections.

Performance Expectancy, PE

In the context of LLM, performance expectancy is the extent to which instructional designers and instructors believe that using LLMs will enhance their productivity. For instructional designers and instructors, using LLMs to create video, image, and content saves time and effort (Hennekeuser et al., 2025; Ivanov & Soliman, 2023; Pereira et al., 2024; Sallam, 2023). Nevertheless, Kumar et al. (2024), Luo et al. (2025), and Yang and Stefaniak (2025) reported that instructional designers conscientiously exercise a cautious approach to ethical concerns about creating images using LLMs because of copyright infringement concerns. As digital assistants, LLMs can be used virtually for all the requirements of instructional design, from brainstorming to the final product, thus signifying their usefulness (Melián-González et al., 2021; Sallam, 2023). However, human oversight is needed to mitigate biases (Pereira et al., 2024; Yadav, 2023). Al-Emran et al. (2024) reported that performance expectancy influenced the behavioural use of AI chatbots in knowledge sharing. Ayanwale et al. (2022) stated that performance expectancy influenced behavioural intention for teachers and students to use an AI chatbot. Several authors (Bhat et al., 2024; Camilleri, 2024; Shahzad et al., 2024; Soodan et al., 2024; Strzelecki, 2023) posited that performance expectancy influenced the behavioural intention to use ChatGPT in higher education. In a study by McNeill et al. (2025), performance expectancy emerged as the primary driver of LLM adoption, signifying its importance in instructional design.

Effort Expectancy, EE

In the context of LLMs, effort expectancy is the extent to which instructional designers and instructors find using LLMs easy. According to Menon and Shilpa (2023), LLMs are easy to use because of their user-friendly, intuitive interface. On the contrary, LLM models may not be easy to use because of the difficulty with prompt engineering that the instructional designers and instructors face. For instance, McNeill et al. (2025) reported that instructional designers spent time and effort to develop prompts that worked adequately in generating reliable answers, hence creating a negative effort expectancy that could inhibit LLM adoption. In previous studies, effort expectancy influenced the use of AI chatbots (Al-Emran et al., 2024; Bhat et al., 2024; Camilleri, 2024; García de Blanes Sebastián et al., 2022; Shahzad et al., 2024; Strzelecki, 2023), but on the contrary, effort expectancy did not influence AI chatbot use (Menon & Shilpa, 2023).

Social Influence, SI

In the context of LLMs, social influence is how instructional designers and instructors believe their significant others influence them to use LLMs. In this study, social influence was divided into social norms and descriptive norms. Social norms are due to the people being influenced by the significant others who could be their peers (Venkatesh et al., 2003), and descriptive norms are due to the modelling behaviours of their peers (De Leeuw et al., 2015). For instance, if someone practically uses LLMs (modelling), their peers can also follow suit. Camilleri (2024) and García de Blanes Sebastián et al. (2022) reported that social influence influenced behavioural intention to use ChatGPT. However, in a study by Bhat et al. (2024), social influence did not influence behavioural intention to use an LLM because teaching academics tend to work as individuals when using ChatGPT. In Al-Emran et al.'s (2024) study on factors that influence knowledge sharing in AI chatbots, social influence did not influence the AI-based chatbots for knowledge sharing, whereas in studies by Melián-González et al. (2021) and Strzelecki (2023), social influence influenced AI chatbot usage. Filipec and Woithe (2023) posited that peer influence and fear of missing out will drive instructional designers to adopt LLMs such as ChatGPT.

Facilitating Conditions, FC

In the context of LLMs facilitating conditions, the instructional designers and instructors believe that organisational and technical support exists to support them using LLMs. Menon and Shilpa (2023) and McNeill et al. (2025) reported that facilitating conditions were very influential in adopting LLMs. For instance, the availability of connectivity ensures access to LLMs, and the converse holds. McNeill et al. (2025) stated that organizational barriers often emerged as the primary obstacle to LLM use. Bhat et al. (2024) posited that facilitating conditions influenced the intention to adopt ChatGPT among lecturers in higher education. Nonetheless, for García de Blanes Sebastián et al. (2022) and Strzelecki (2023), facilitating conditions did not influence behavioural intention to use virtual assistants and ChatGPT, respectively. Al-Emran et al. (2024) indicated that facilitating conditions did not influence AI-based chatbots for knowledge-sharing use. However, facilitating conditions influenced the behavioural use of ChatGPT (Strzelecki, 2023).

Habit, H

In the context of LLMs, habit is how instructional designers and instructors have acquired regular and consistent patterns of using LLMs. According to Bhat et al. (2024), instructional designers or university-teaching academics who habitually use technology in their teaching practices are more likely to adopt novel technologies. Bhat et al. (2024), García de Blanes Sebastián et al. (2022), and Strzelecki (2023) found that habit influenced behavioural intention to use ChatGPT. Several authors have posited that habits influence the behavioural use of chatbots (Al-Emran et al., 2024; Melián-González et al., 2021; Strzelecki, 2023).

Hedonic Motivation, HM

In the context of LLMs, hedonic motivation is the joy instructional designers and instructors derive from using them. The influence of hedonic motivation on the use of chatbots has been mixed. Bhat et al. (2024) and Strzelecki (2023) reported that hedonic motivation influenced behavioural intention to adopt ChatGPT among teaching academics in higher education. Melián-González et al. (2021) reported that hedonic motivation influenced AI travel chatbot use. On the contrary, hedonic motivation did not influence the use of AI chatbots (Al-Emran et al., 2024; García de Blanes Sebastián et al., 2022).

Personal Innovativeness, PI

In the context of LLMs, Personal Innovativeness is the willingness of instructional designers and instructors to experiment and use LLMs. García de Blanes Sebastián et al. (2022) and Strzelecki (2023) reported that personal innovativeness influenced behavioural intention to use virtual assistants and ChatGPT, respectively, while Melián-González et al. (2021) reported that personal innovativeness influenced chatbot usage. However, personal innovativeness did not influence behavioural intention to adopt LLMs among lecturers in higher education (Bhat et al., 2024). In addition, Kumar et al. (2024), Luo et al. (2025), and Yang and Stefaniak (2025) reported that instructional designers were hesitant and skeptical about using LLMs, which, in turn, hindered the development of their personal innovativeness.

Behavioural intention, BI, and behavioural use, BU

In this context, behavioural intention is the extent to which instructional designers and instructors intend to use LLMS. In this study, use behaviour is the extent of instructional designers' and instructors' actual usage of LLMs. According to Strzelecki (2023) and Bhat et al. (2024), behavioural intention influenced the use of ChatGPT in higher education

Trust in LLM provider, TP

In this study, trust in the provider refers to the extent to which instructional designers and instructors believed they could trust the LLM provider. Marr (2024) recently reported a downward shift in public trust in AI. This downward shift in trust may cause instructional designers and instructors to stop using LLMs.

Trust in LLMs, TT

In this study, trust is the extent to which instructional designers and instructors believe they can trust LLMs. Lack of trust and blind trust influence how individual users interact with AI tools (Amoozadeh et al., 2024). García de Blanes Sebastián et al. (2022) reported that for emerging technologies, users feel uncertain due to a lack of information, but with more use, they can then trust the LLMs. The lack of output explainability (step-by-step explanations of reasoning) in the answers provided by some LLMs fuels mistrust (Hennekeuser et al., 2025). In addition, the fact that LLMs are biased and hallucinate forces users not to trust them (Beale, 2025; Chang et al., 2023; Leiker et al., 2023; Moore et al., 2023; Strzelecki, 2023; Y. Wang et al., 2023). Choung et al. (2022) and García de Blanes Sebastián et al. (2022) posited that trust influenced behavioural intention to use AI and virtual assistants. However, Bhat et al. (2024) reported that trust did not influence the behavioural use of ChatGPT. In addition, Kumar et al. (2024), Luo et al. (2025), and Yang and Stefaniak (2025) posited that instructional designers exhibited hesitation and skepticism toward the use of large language models (LLMs), primarily due to concerns about potential copyright infringement, especially when generating images. Yang and Stefaniak (2025) also posited that mistrust is a result of apprehension about the potential displacement of traditional design skills.

METHODOLOGY

MEASURES

We used a cross-sectional correlational quantitative study. A cross-sectional correlational quantitative design provides a 'snapshot' of the phenomenon under study and allows the relationship between the variables to be determined (Kesmodel, 2018). The cross-sectional correlational design was selected because the results can be generalized to a larger population, and it is inexpensive and easy to run, unlike a longitudinal study (Spector, 2019). The measuring instrument was adapted from Farooq et al.'s (2017) UTAUT3 framework. It was then modified to suit the LLM context by adding trust in technology and trust in technology providers as additional constructs. The questionnaire used a 7-point Likert scale (1 = strongly disagree and 7 = strongly agree) for all items. We used a purposive sampling method to target instructional designers in colleges and universities across the globe.

DATA COLLECTION

An online survey tool was used to collect data. We also collected biographical information, including age, gender, type of LLM used, learning design experience, working setting, and the country where the instructional designers or instructors were based. The link to the survey was posted on various social media, including the LinkedIn and Facebook profiles of the three authors for reposting. In addition, the survey was distributed to instructional designers in South Africa via their professional forum and email list, ensuring targeted outreach to practitioners actively engaged in AI-related design work and Science and Technology communities in South African universities.

PARTICIPANTS

The participants were primarily instructional designers and a few teaching academics working in different settings. Apart from South Africa, most participants who responded to the questionnaire were from developed countries, probably indicating easy access to social media. Table 1 shows the frequency and percentages of participants by country.

Table 1. The frequency and percentages of the participants by country

Country	Number of respondents	Percentage
South Africa	109	53.7
United States	17	8.4
United Kingdom	16	7.9
Portugal	7	3.4
Poland	6	3
Spain	5	2.5
Italy	5	2.5
Greece	5	2.5
India	5	2.5
Netherlands	4	2
Australia	4	2
Canada	4	2
Japan	3	1.5
**	13	5.5
Total	203	100

** denotes countries with less than 3 participants: Austria, Finland, Ireland, Estonia, Israel, Saudi Arabia, Vietnam, Hungary, Venezuela, Germany and Thailand.

Table 2 shows the distribution of the instructional designers according to gender, age, design experience, work setting, qualification, and the types of LLMs they used. The common age group was 26-35. Average design experience was between 3 and 5 years. Most of the participants were either working at a university/college or an education technology company. Many of the participants had a master's degree. Most of the participants used ChatGPT3 (55.7%), followed by ChatGPT4 (20.7%). However, 17.7% of the participants had not used large language models for learning design purposes.

Table 2. The characteristics of participants

Variable		Frequency	Percentage
Gender	Female	126	62.1
	Male	77	37.9
Age	18 - 25	25	12.3
	26 - 35	100	49.3
	36 - 45	39	19.2
	46 - 55	29	14.3
	56 - 65	8	3.9
	> 65	2	1.0
Design experience	< 1	28	13.8
	1 - 2	43	21.2
	3 - 5	53	26.1
	6 - 10	40	19.7
	11 - 15	20	9.9
	16 - 20	9	4.4
	> 21	10	4.9
Work setting	College/university	65	32.0
	Corporate world	21	10.3
	Education technology	52	25.6
	Government/non-profit	10	4.9
	Freelance	19	9.4
Qualification	High School	7	3.4
	Certificate/diploma	10	4.9
	Bachelors	53	26.1
	Honours	38	18.7
	Masters	68	33.5
	Doctorate	27	13.3
LLM type	Bard	1	0.5
	Bing	8	3.9
	ChatGPT3	113	55.7
	ChatGPT4	42	20.7
	Other	3	1.5
	Not yet	36	17.7
Total		203	

DATA ANALYSIS

EXPLORATORY FACTOR ANALYSIS

The Statistical Packages for Social Science (SPSS) and Analysis of Moment Structures (AMOS) version 29 were used to analyse the data. Exploratory factor analysis using principal axial factoring was used to validate the questionnaire adapted from Farooq et al. (2017). The Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) was determined first to check whether factor analysis was plausible. The KMO for all constructs was 0.924, exceeding the minimum threshold of 0.5, indicating a strong result (Backhaus et al., 2016). To check for common method or self-bias in the questionnaire, Harman's single-factor test was used. All variables loaded onto a single factor, accounting for 38.960% of the explained variance, which is less than 50%, thus demonstrating the absence of common method bias (Dupuis et al., 2017).

The exploratory factor analysis was used to check the unidimensionality (grouping of related items) of the items of the variables. Based on eigenvalues larger than one, seven factors accounting for 69,928% of the explained variance were extracted from the factor analysis. Table 3 shows the exploratory factor analysis results. In factor 1, the items for trust in LLM providers merged with those of trust in LLMs and were labelled "Reliability & Provider Trust in LLMs" (TPTT). In factor 2, the items of performance expectancy, behavioural intention, and behavioural use merged and were named "Perceived LLM Benefits & Usage" (PEBIBU). In factor 3, the items of effort expectancy, facilitating conditions, and motivation merged and were named "Ease of Use & Support" (EFH). In factor 4, the personal innovativeness items were distinct and named "Innovative Propensity towards LLM Adoption" (PI). Items in factor 5 of descriptive norms merged with facilitating conditions and were named "Community Standards & Infrastructure" (SF). In factor 6, the items of habit were distinct and were named "Ingrained LLM Practices" (HM). Finally, the items of factor 7 (S1, S2, S3) were distinct and were named "LLM Peer-Driven Expectations" (SI). The naming of the factors was guided by considering items with the highest factor loadings, followed by middle and lowest loadings. For instance, items of trust in the provider had higher loadings than trust in LMS, hence TPTT.

Table 3. The exploratory factor analysis for all the constructs

	Factor						
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**
TP1	0.928						
TT4	0.857						
TP2	0.849						
TP4	0.846						
TT3	0.765						
TT1	0.689						
TP3	0.627						
TT2	0.594						
PE2		0.943					
PE1		0.852					
BI1		0.845					
PE3		0.843					
BI3		0.819					
PE4		0.726					
BU1		0.643					

	Factor						
Items	**1**	**2**	**3**	**4**	**5**	**6**	**7**
BU2		0.549					
BI2		0.513					
EE1			0.918				
EE2			0.874				
FC2			0.734				
EE4			0.726				
EE3			0.677				
HM2			0.405				
HM1							
FC3							
PI3				0.883			
P11				0.878			
PI4				0.781			
PI2				0.754			
HM3							
SI4					0.775		
SI5					0.755		
FC4					0.716		
SI6					0.458		
FC1			0.404		0.406		
H2						0.823	
H3						0.698	
H1						0.565	
H4						0.417	
SI1							0.774
SI2							0.701
SI3							0.689

Multicollinearity

The correlations of the factors were less than 0.8, indicating no multicollinearity in the extracted factors (Barton & Peat, 2014). Table 4 shows the correlations among the constructs.

Table 4. The correlation matrix of the factors

Factor	1	2	3	4	5	6	7
1	1.000						
2	0.611	1.000					
3	0.408	0.565	1.000				
4	0.439	0.620	0.658	1.000			
5	0.418	0.489	0.424	0.374	1.000		
6	0.484	0.485	0.191	0.250	0.428	1.000	
7	0.398	0.504	0.392	0.362	0.251	0.159	1.000

Reliability

Reliability measures the internal consistency of the related constructs. Cronbach's alpha was used to measure internal consistency. The Cronbach's alpha values for all the constructs were greater than 0.8, thus demonstrating excellent internal consistency (Tavakol & Dennick, 2011). Table 5 shows the Cronbach's alpha for the related constructs

Table 5. The Cronbach's alpha for the related constructs

Construct	Cronbach's alpha	# of items
Reliability & Provider Trust in LLMs (TPTT)	0.921	8
Perceived LLM Benefits & Usage (PEBIBU)	0.939	9
Ease of Use & Support (EFH)	0.901	5
Innovative Propensity towards LLM Adoption (PI)	0.865	4
Community Standards & Infrastructure (SF)	0.813	3
Ingrained LLM Practices (HM)	0.861	3
LLM Peer-Driven Expectations (SI)	0.856	3
ALL ITEMS	0.959	42

Construct validity

Construct validity comprises convergent and discriminant validity, where convergent validity measures the degree of relatedness of items in a construct, and discriminant validity measures the degree of distinctiveness of items across constructs (Clark & Watson, 2019). We used composite reliability (CR) and Average variance extracted (AVE) to measure convergent validity. The CR and AVE values for all the constructs were greater than 0.7 and 0.5, respectively, demonstrating convergent validity (Hair et al., 2006). For discriminant validity, the square roots of AVE values (bold) were greater than the inter-construct correlations, demonstrating discriminant validity for all the constructs (Fornell & Larcker, 1981). Table 6 shows the convergent and discriminant values.

Table 6. Measurement of convergent and discriminant validity

	CR	AVE	1	2	3	4	5	6	7
1	0.923	0.605	**0.778**						
2	0.923	0.579	0.611	**0.761**					
3	0.892	0.626	0.408	0.565	**0.791**				
4	0.895	0.683	0.439	0.620	0.658	**0.826**			
5	0.869	0.688	0.418	0.489	0.424	0.374	**0.829**		
6	0.741	0.494	0.484	0.485	0.191	0.250	0.428	**0.703**	
7	0.765	0.522	0.398	0.504	0.392	0.362	0.251	0.159	**0.772**

CONFIRMATORY FACTOR ANALYSIS

Confirmatory factor analysis was undertaken using AMOS version 29 to verify the measurement model. All the items retained had factor loadings greater than 0.6, indicating convergent validity (Field, 2018). Item TP3 was dropped to improve model fitness. Items HM1, FC3, and HM3 cross-loaded on two factors and were dropped from the analysis. Figure 3 shows the confirmatory factor analysis model.

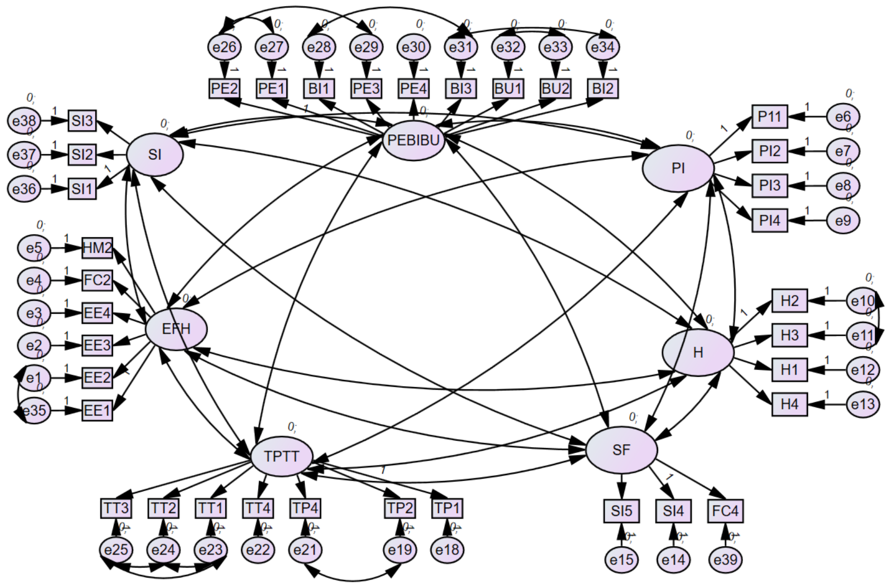

Figure 3. The confirmatory factor analysis model

Model fitness

The fit indices used to determine the fit of the model were the comparative fit index (CFI), the root mean square error of approximation (RMSEA), the chi-square value (CMIN), the Tucker-Lewis index (TLI), the Incremental Fit Index (IFI), and the degrees of freedom (df). The CFI (0.926), TLI (0.917), and IFI (0.927) were greater than 0.90, indicating a reasonable fit. The CMIN/df was equal to 1.734, consistent with values between 1 and 3, and RMSEA was equal to 0.060, less than 0.08, indicating a good fit (Hu & Bentler, 1999).

Structural analysis

Structural equation modelling was then employed to determine the relationships among the constructs. Compared with the UTAUT3 framework elements, factor PEBIBU was regarded as the dependent variable and the other variables (SI, EFH, TPTT, SF, H, and PI) as predictors. The following hypotheses were generated:

- **H1:** LLM peer-driven expectations (SI) influenced perceived LLM benefits and usage (PEBIBU)
- **H2:** Community standards and infrastructure (SF) influenced Perceived LLM benefits and usage (PEBIBU)
- **H3:** Ingrained LLM practices (H) influenced perceived LLM benefits and usage (PEBIBU)
- **H4:** Reliability and provider Trust in LLMs (TPTT) influenced perceived LLM benefits and usage (PEBIBU)
- **H5:** Ease of use and support (EFH) influenced perceived LLM benefits and usage (PEBIBU)
- **H6:** Innovative Propensity towards LLM Adoption (PI) influenced perceived LLM benefits and usage (PEBIBU)

Figure 4 shows the structural analysis model. All the predictors (SI, EFH, TPTT, SF, H, PI) except SF (which is primarily descriptive norms) had a statistically significant influence on PEBIBU. Table 7 shows the relationship between the constructs. The PEBIBU construct accounted for 76.4% of the explained variance due to its predictors.

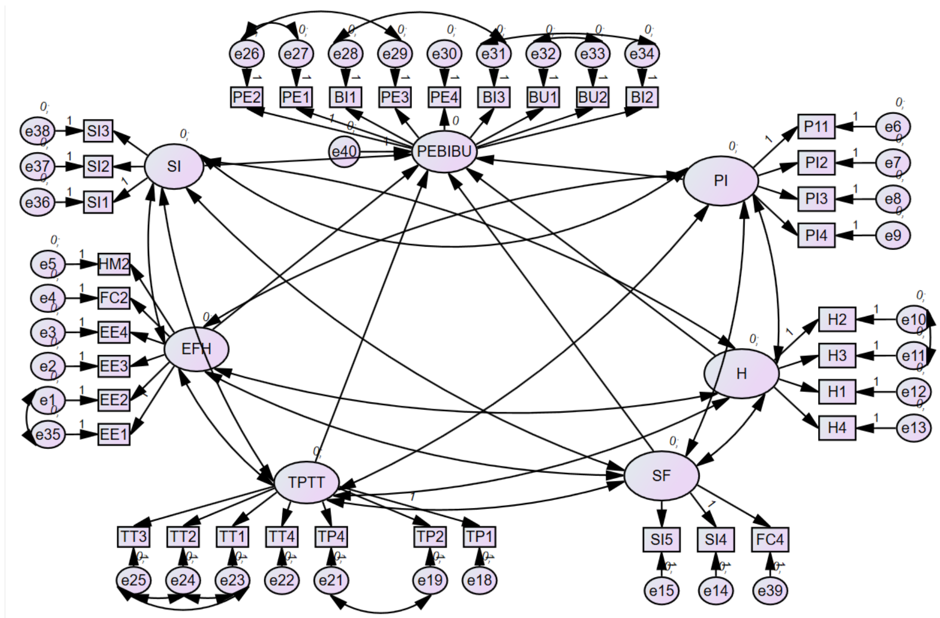

Figure 4. The structural analysis models

Table 7. Hypothesis test results

Hypotheses	Path			Standardised estimate	P	Result
H3	PEBIBU	<---	H	0.396	***	Supported
H1	PEBIBU	<---	SI	0.293	***	Supported
H6	PEBIBU	<---	PI	0.190	0.012	Supported
H4	PEBIBU	<---	TPTT	0.136	0.030	Supported
H5	PEBIBU	<---	EFH	0.159	0.039	Supported
H2	PEBIBU	<---	SF	-0.049	0.467	Not supported

Second Order Confirmatory Factor Analysis

From the correlations in Table 4, factors 1, 2, 3, and 4 are all moderately to highly correlated with each other, suggesting the presence of a common underlying higher-order factor. Factors 5, 6, and 7 are also lowly correlated with each other, indicating the presence of a second high-order factor. In addition, the second-order structural equation modelling was undertaken on the basis that it captures the holistic concept of engagement with LLMs as represented by the integration of performance expectancy (PE), behavioural intention (BI), and behavioural use (BU) to form the PEBIBU construct, which was named "Perceived LLM Benefits & Usage". The main second-order latent factor was named "Learning Design", and its sub-construct was named "Supportive conditions and external influences" (SC_EI). Figure 5 shows the two second-order latent factors: Learning Design and its sub-construct, supportive conditions and external influences (SC_EI).

SC_EI contributes most to the learning design since its explained variance is 94.4%, followed by PEBIBU at 88.1%, followed in third place by EFHM at 44.9%, followed by PI at 40.9 % and TPTT at 38.3%. For supportive conditions and external influences, the habit construct contributed 73.4%, followed by SI (social norms) at 42.8% and SF (descriptive norms and facilitating conditions) at 36.6%. Table 8 shows the significant contribution of the elements to Learning design and the sub-construct of social conditions and external influence (SC_EI).

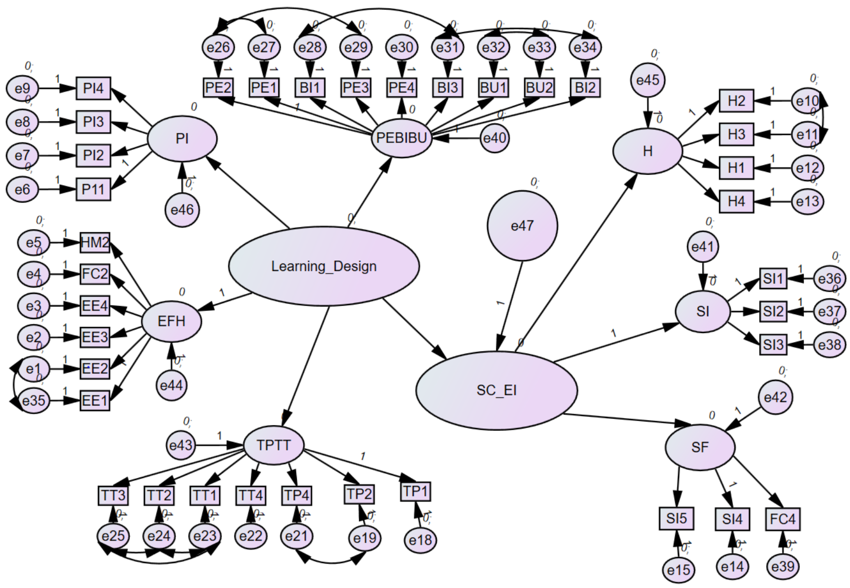

Figure 5. The second-order structural equation model

Table 8. Contributions to learning design, social conditions, and external influence

Relationship			Estimate	SE	CR	P	Explained variance	Rank	Interpretation
SC_EI	<---	Learning Design	0.972	0.156	6.470	***	94.4	1	Significant
PEBIBU	<---	Learning Design	0.939	0.146	7.944	***	88.1	2	Significant
EFH	<---	Learning Design	0.670				44.9	3	Significant
PI	<---	Learning Design	0.639	0.127	6.726	***	40.9	4	Significant
TPTT	<---	Learning Design	0.619	0.189	6.924	***	38.3	5	Significant
H	<---	SC_EI	0.856	0.206	7.025	***	73.4	1	Significant
SI	<---	SC_EI	0.654				42.8	2	Significant
SF	<---	SC_EI	0.605	0.191	6.048	***	36.6	3	Significant

INFLUENCE OF MODERATORS

The ANOVA test was conducted to test the effect of moderators on the variables. Gender influenced innovative propensity towards LLM adoption (PI), with the mean of males being greater than that of females. Age did not influence all constructs. Region type influenced "Community Standards & Infrastructure" (SF), where the Tukey post hoc test indicated that instructional designers and instructors in South Africa had a statistically significant mean greater than their Asian counterparts. Qualifications influenced TPTT and Habit. For the TPTT construct, the Tukey post hoc test indicated that a bachelor's qualification had a statistically significant higher mean than honours, master's, and doctorate qualifications.

DISCUSSION

This study investigated the factors influencing the adoption of LLMs by instructional designers and instructors in different countries. The factor structure of the LLMs did not perfectly align with the UTAUT3 model. For instance, performance expectancy, behavioural intention, and behavioural use merged into one factor, probably indicating LLMs' unique nature in learning design. However, habit, social norms, and personal innovativeness remained as distinct entities, aligning with the UTAUT3.

THE FACTORS INFLUENCING THE BEHAVIOURAL INTENTION AND USE OF LARGE LANGUAGE MODELS (LLMS)

Ingrained LLM Practices (habit) had a statistically significant effect on perceived LLM benefits and usage. This result is consistent with findings from several authors (Bhat et al., 2024; García de Blanes Sebastián et al., 2022; Strzelecki, 2023), who reported that habit influenced behavioural intention to use ChatGPT. The result is also consistent with findings from several authors who posited that habit influences the behavioural use of chatbots (Al-Emran et al., 2024; Melián-González et al., 2021; Strzelecki, 2023). The two findings resonate with Bhat et al.'s (2024) findings that instructional designers or university-teaching academics who habitually use technology in their teaching practices are more likely to adopt novel technologies. LLM Peer-Driven Expectations (social norms) had a statistically significant influence on perceived LLM benefits and use. This result is consistent with findings from Camilleri (2024) and García de Blanes Sebastián et al. (2022), who stated that social influence influenced behavioural intention to use ChatGPT, but is inconsistent with findings from Bhat et al. (2024). In addition, the result is consistent with findings from Melián-González et al. (2021) and Strzelecki (2023), who posited that social influence influenced AI chatbot usage, and is inconsistent with findings from Al-Emran et al. (2024). The positive results on usage align with findings from Filipec and Woithe (2023), who posited that peer influence and fear of missing out would drive instructional designers and instructors to adopt LLMs.

Innovative Propensity towards LLM Adoption (personal innovativeness, PI) significantly influenced perceived LLM benefits and usage (PEBIBU). This result agrees with findings from García de Blanes Sebastián et al. (2022), Melián-González et al. (2021), and Strzelecki (2023), who reported that PI influenced behavioural intention to use ChatGPT. Nevertheless, this result is inconsistent with the findings of Bhat et al. (2024) and Kumar et al. (2024), who reported that instructional designers were hesitant and skeptical about using LLMs, which in turn hindered the development of their personal innovativeness. Reliability and provider trust in LLMs (TPTT) influenced LLM benefits and usage (PEBIBU). This result aligns with findings from Choung et al. (2022) and García de Blanes Sebastián et al. (2022), who reported that trust influenced behavioural intention to use AI, but is inconsistent with findings from Bhat et al. (2024) and Marr (2024).

Ease of use and support (EFH) influenced perceived LLM benefits and usage (PEBIBU). This result is consistent with findings from several authors (Al-Emran et al., 2024; Bhat et al., 2024; Camilleri, 2024; Shahzad et al., 2024) but resonates with the findings of McNeill et al. (2025), who reported that prompt engineering created barriers to LLM adoption when instructional designers spent time and effort to develop prompts that worked adequately in generating reliable answers. Nonetheless, the result is inconsistent with findings from Menon and Shilpa (2023). Community standards and infrastructure (descriptive norms, SF) had a statistically insignificant effect on perceived LLM benefits and usage (PEBIBU), signifying that the participants who took part in the study were mainly from developed countries and had access to connectivity and LLMs. In addition, the insignificance of SF (descriptive norms) can also be attributed to trust issues, a lack of which leads to poor peer modelling behaviours. Consequently, a lack of trust breeds skepticism, which breeds poor modelling behaviours, leading to poor acceptance of LLMs, thus aligning with findings from Sridhar et al. (2023).

Contribution to Learning Design

The second-order confirmatory factor analysis revealed one major latent variable, learning design, and a subconstruct, supportive conditions and external influences (SC_EI). SC_EI contributed most to the learning design, accounting for 94.4% of the explained variance with its subcomponent, habit, accounting for the most explained variance (73.4%) as an individual construct ahead of social and descriptive norms. This result reinforces findings from Bhat et al. (2024) and Melián-González et al. (2021), who emphasised the importance of habit in adopting LLMs. Perceived LLM Benefits and Usage (PEBIBU) contributed the second most explained variance to learning design (88.1%), signifying that when the instructional designers and instructors perceive the LLMs to be useful, the intention to use them is turned into actual use in real-time, the same reason for their merging to form the PEBIBU construct. This result aligns with findings from many authors who reported how LLMs enhance productivity and save time (Al-Emran et al., 2024; Alkafaween et al., 2025; Ayanwale et al., 2022; Hennekeuser et al., 2025; Ivanov & Soliman, 2023; Melián-González et al., 2021; Pereira et al., 2024; Sallam, 2023). The Ease of Use and Support (EFH) contributed the third most variance to learning design, aligning with findings from Menon and Shilpa (2023), who reported that LLMs were easy to use because of their user-friendly and intuitive interface. However, beyond a user-friendly and intuitive interface, there is a challenge of prompting engineering when instructional designers spend time and effort to develop prompts that work adequately (McNeill et al., 2025), suggesting that LLMs are not easy to use, and a lack of good prompting skills deters LLM adoption.

The propensity towards LLM Adoption (PI) was ranked fourth on its contribution to learning design, indicating that instructional designers and teaching academics were not experimenting enough to keep up with the ever-changing evolution of the LLMs. This result aligns with Kumar et al. (2024), McNeill et al. (2025), and Yang and Stefaniak's (2025) findings that instructional designers maintain a cautious outlook toward LLM reliability because of their hallucinations, bias, and concerns about the quality of the generated content (Luo et al., 2025). It is worth noting that personal innovativeness cannot flourish in an environment of mistrust, aligning with the views of Kasneci et al. (2023) and Pan et al. (2023). Reliability and provider trust in LLMs (TPTT) contributed the least to learning design, underpinning the problems such as hallucinations, copyright violations, and plagiarism issues, which are still plaguing LLMs (Chang et al., 2023; Leiker et al., 2023; McNeill et al., 2025; Strzelecki, 2023; Tam et al., 2023). This result aligns with the findings of Kozan et al. (2025), McNeill et al. (2025), and Yang and Stefaniak (2025), that instructional designers maintain a cautious outlook toward LLM reliability.

The Influence of Moderators

The means for the males were greater and statistically significant than those of the females. This result is consistent with findings from Draxler et al. (2023). Age did not influence all constructs, which is inconsistent with findings from Draxler et al. (2023), where young people had an edge over older people in LMS usage. Instructional designers and teaching academics in South Africa had a statistically significant mean greater than their Asian counterparts for SF, probably because South Africa is a non-collectivist culture, and the influence of the significant other is more pronounced compared to collectivist Asian cultures. Surprisingly, a bachelor's qualification had a greater and statistically significant mean than an honours, master's, and doctorate qualification for TPTT, suggesting that postgraduate holders were more skeptical than those with a first degree.

Implications

Practical Implications

This study provides a starting point for evaluating the factors that influence the acceptance and use of LLMs by instructional designers and teaching academics and their impact on learning design. Universities can craft intervention strategies that can be used to improve LLM acceptance by instructional designers and teaching academics to improve the learning experience and enhance productivity. For instance, "Supportive conditions and external influences" (SC_EI) contributed most to the learning design, with its components of habit accounting for the most explained variance (73.4%), indicating that the universities must cultivate the habits of the instructional designers and teaching academics by organising regular workshops on LLMs, their applications, and best practices.

In addition, the universities must encourage using LLMs in designing content, assessments, and interactive learning activities, which university teaching academics find time-consuming (Hennekeuser et al., 2025; Pereira et al., 2024; Yang & Stefaniak, 2025). Further creation of a supportive community where instructional designers and teaching academics can share experiences is needed. Reliability and provider Trust in LLMs (TPTT) contributed the lowest explained variance, paving the way to build the trust of the instructional designers and teaching academics through workshops on prompting and responsible and ethical use of LLMs (Yang & Stefaniak, 2025) and showcasing case studies where LLMs have been integrated into learning design successfully. PI also contributed the least variance to learning design, indicating that the universities could conduct workshops on the creative and innovative use of LLMs. Finally, universities must ensure that instructional designers have access to the tools to experiment with LLMs by subscribing to Microsoft Copilot and ChatGPT premier services. Instructional designers and teaching academics must be encouraged to use LLMs as digital assistants. All the listed interventions above will lead to learning design gains, student engagement, and positive learning outcomes.

Theoretical Contributions

A new factor structure emerged when applying the UTAUT3 to instructional designers' and university teaching staff's acceptance and use of LLMs. For instance, the perceived benefits and usage factor emerged from the combination of performance expectancy, behavioural intention, and behavioural use. These constructs (PE, BI, BU) are normally distinct entities in many previous UTAUT1/2/3 applications. This could mean that the UTAUT3 framework may need to be modified for instructional designers and instructors to be relevant in adopting LLMs. New variables, trust in using LLMs and trust in LLM providers, were added to the UTAUT3, thus extending the UTAUT3 in the learning design landscape.

Limitations and Future Research

Although the sample was derived from several countries, the number of participants from countries other than South Africa was low. The low number from these countries is a cause for concern since the sample is not representative of any usage of LLMs in any country. A quantitative study was employed, but it failed to capture the rich tapestry of data available through a mixed method.

For future studies, more studies are needed to verify the factor structure of LLMs for instructional designers and teaching academics in different settings. Since LLMs are continuously evolving and gaining more traction, a longitudinal study should be employed to determine whether the factor structure of LLMs using the UTAUT3 remains the same or changes with time. Further qualitative studies must be undertaken to gain deeper insights into the factors influencing the adoption of LLMs. It is also important to include prior training in using LLMs as a moderator to distinguish whether training influences the adoption of LLMs.

Conclusions

This study investigates the factors influencing the adoption of LLMs by instructional designers and instructors. The following research questions guided the study:

- What factors influence instructional designers' and instructors' behavioural intentions and use of LLMs in learning design?

- How do the resultant individual factors contribute to Learning design?
- How do factors like age, gender, and qualification moderate the variables in LLM adoption?

The exploratory factor analysis revealed a unique factor structure for the LLM adoption by instructional designers and instructors where items of performance expectancy, behavioural intention and behavioural use merged to form the Perceived LLM Benefits and Usage (PEBIBU) construct suggesting that performance expectancy(usefulness), behavioural intention and behavioural use in LMS usage have a unique relatedness, where the perception of usefulness directly translates to intention and use without clear demarcation unlike the usually distinct entities in the UTAUT3 theory.

The structural analysis results indicate that ingrained LLM practices (habits), LLM peer-driven expectations (SI), innovative propensity towards LLM adoption (personal innovativeness), reliability and provider trust in LLMs (trust), ease of use and support (combined effort expectancy and facilitating condition) influenced perceived benefits and usage of LLMs (PEBIBU). Community standards and infrastructure (social influence and facilitating conditions combined) did not influence perceived LLM benefits and usage, probably because the participants were from developed countries with well-developed connectivity infrastructure. Nevertheless, community standards and infrastructure will likely be significant in developing countries with problematic connectivity, magnifying the digital divide between rich and poor countries.

The second-order structural equation modelling indicated that supportive conditions and external influence (habit, social influence, and facilitating conditions combined), dominated by the habit construct, contributed most to learning design, emphasizing the importance of ingrained habits as the strongest predictor of learning design, suggesting the need for regular use of LLMs by instructional designers and teaching academics.

Perceived LLM benefits and usage contributed the second most to learning design, emphasizing the need to align perceived LLM benefits and usage with student learning outcomes in teaching and learning to support student retention and assessment. Ease of use and support contributed the third most variance to learning design, indicating the importance of training to make using LLMs easy through good prompting skills. Hence, universities must provide courses on prompting engineering or workshops to empower their staff and integrate LLMs into existing workflows or teaching processes. The innovative propensity towards LLM adoption (personal innovativeness) contributed the fourth most to learning design, suggesting that instructional designers and instructors are reluctant to experiment with new technologies; hence, universities must create enabling environments for structured experimentation by leveraging early adopters to lead workshops or provide peer mentorship. Reliability and provider trust in LLMs (Trust in Provider and Trust in LMS) contributed the least to learning design for instructional designers and instructors, signifying the need for universities to provide transparent use of personal data, training, and responsible and ethical use of LLMs to build trust. Understanding the contribution to learning design by individual factors helps instructional designers and instructors develop support strategies and interventions to improve learning design experiences and hence learning outcomes. Regarding gender, males had a stronger usage of LLMs compared to females. Age did not influence LLM usage. Instructional designers and teaching academics with postgraduate qualifications were more skeptical of LLM usage than those with a first degree.

REFERENCES

Abd-alrazaq, A., AlSaad, R., Alhuwail, D., Ahmed, A., Healy, P. M., Latifi, S., Aziz, S., Damseh, R., Alabed Alrazak, S., & Sheikh, J. (2023). Large language models in medical education: Opportunities, challenges, and future directions. *JMIR Medical Education*, *9*, e48291. https://doi.org/10.2196/48291

Al-Emran, M., AlQudah, A. A., Abbasi, G. A., Al-Sharafi, M. A., & Iranmanesh, M. (2024). Determinants of using AI-based chatbots for knowledge sharing: Evidence from PLS-SEM and fuzzy sets (fsQCA). *IEEE Transactions on Engineering Management. 71*, 4985-4999. https://doi.org/10.1109/TEM.2023.3237789

Alkafaween, U., Albluwi, I., & Denny, P. (2025). Automating autograding: Large language models as test suite generators for introductory programming. *Journal of Computer Assisted Learning*, *41*(1), e13100. https://doi.org/10.1111/jcal.13100

Amoozadeh, M., Daniels, D., Nam, D., Kumar, A., Chen, S., Hilton, M., Srinivasa Ragavan, S., & Alipour, M. A. (2024). Trust in Generative AI among students: An exploratory study. *Proceedings of the 55th ACM Technical Symposium on Computer Science Education* (pp. 67-73). Association for Computing Machinery. https://doi.org/10.1145/3626252.3630842

Avedzi, J. E. (2025). *"When algorithms teach": A quantitative analysis of instructional designers' perceptions of fairness, accountability, and data privacy in artificial intelligence integration.* https://doi.org/10.21203/rs.3.rs-7349948/v1

Ayanwale, M. A., & Molefi, R. R. (2024). Exploring intention of undergraduate students to embrace chatbots: From the vantage point of Lesotho. *International Journal of Educational Technology in Higher Education*, *21*, Article 20. https://doi.org/10.1186/s41239-024-00451-8

Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence*, *3*, 100099. https://doi.org/10.1016/j.caeai.2022.100099

Backhaus, K., Erichson, B., Plinke, W., & Weiber, R. (2016). *Multivariate analysemethoden.* Springer. https://doi.org/10.1007/978-3-662-46076-4

Barton, B., & Peat, J. (2014). *Medical statistics: A guide to SPSS, data analysis and critical appraisal.* Wiley.

Baytak, A. (2023). The acceptance and diffusion of generative artificial intelligence in education: A literature review. *Current Perspectives in Educational Research*, *6*(1), 7-18. https://doi.org/10.46303/cuper.2023.2

Beale, R. (2025). *The revolution has arrived: What the current state of large language models in education implies for the future.* PsyArXiv. https://doi.org/10.48550/arXiv.2507.02180

Bećirović, S. (2023). Challenges and barriers for effective integration of technologies into teaching and learning. *Digital pedagogy: The use of digital technologies in contemporary education* (pp. 123-133). Springer. https://doi.org/10.1007/978-981-99-0444-0_10

Bhat, M. A., Tiwari, C. K., Bhaskar, P., & Khan, S. T. (2024). Examining ChatGPT adoption among educators in higher educational institutions using extended UTAUT model. *Journal of Information, Communication and Ethics in Society*, *22*(3), 331-353. https://doi.org/10.1108/JICES-03-2024-0033

Bissessar, C. (2023). To use or not to use ChatGPT and assistive artificial intelligence tools in higher education institutions? The modern-day conundrum – Students' and faculty's perspectives. *Equity in Education & Society*. https://doi.org/10.1177/27526461231215083

Bolick, A. D., & Da Silva, R. L. (2024). Exploring artificial intelligence tools and their potential impact to instructional design workflows and organizational systems. *TechTrends*, *68*, 91-100. https://doi.org/10.1007/s11528-023-00894-2

Bond, M. A., Lockee, B. B., & Blevins, S. J. (2023, October 31). Instructional designers as institutional change agents. *EDUCAUSE Review*. https://er.educause.edu/articles/2023/10/instructional-designers-as-institutional-change-agents

Bonner, E., Lege, R., & Frazier, E. (2023). Large language model-based artificial intelligence in the language classroom: Practical ideas for teaching. *Teaching English with Technology*, *23*(1), 23-41. https://doi.org/10.56297/BKAM1691/WIEO1749

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, *201*, 123247. https://doi.org/10.1016/j.techfore.2024.123247

Chang, Y., Wang, X., Wang, J., Wu, Y., Yang, L., Zhu, K., Chen, H., Yi, X., Wang, C., Wang, Y., Ye, W., Zhang, Y., Chang, Y., Yu, P. S., Yang, Q., & Xie, X. (2023). A survey on evaluation of large language model. *ACM Transactions on Intelligent Systems and Technology*, *15*(3), Article 39. https://doi.org/10.1145/3641289

Choung, H., David, P., & Ross, A. (2022). Trust in AI and its role in the acceptance of AI technologies. *International Journal of Human-Computer Interaction*, *39*(3), 1727-1739. https://doi.org/10.1080/10447318.2022.2050543

Clark, L. A., & Watson, D. (2019). Constructing validity: New developments in creating objective measuring instruments. *Psychological Assessment*, *31*(12), 1412–14270. https://doi.org/10.1037/pas0000626

Davis, R. O., & Lee, Y. J. (2023). Prompt: ChatGPT, create my course, please! *Education Sciences*, *14*(1), 24. https://doi.org/10.3390/educsci14010024

de Fine Licht, K. (2023). Integrating large language models into higher education: Guidelines for effective implementation. *Computer Sciences & Mathematics Forum*, *8*(1), 65. https://doi.org/10.3390/cmsf2023008065

De Leeuw, A., Valois, P., Ajzen, I., & Schmidt, P. (2015). Using the theory of planned behavior to identify key beliefs underlying pro-environmental behavior in high-school students: Implications for educational interventions. *Journal of Environmental Psychology*, *42*, 128-138. https://doi.org/10.1016/j.jenvp.2015.03.005

Draxler, F., Buschek, D., Tavast, M., Hämäläinen, P., Schmidt, A., Kulshrestha, J., & Welsch, R. (2023). *Gender, age, and technology education influence the adoption and appropriation of LLMs.* PsyArXiv. https://doi.org/10.48550/arXiv.2310.06556

Dupuis, M., Khadeer, S., & Huang, J. (2017). "I Got the Job!": An exploratory study examining the psychological factors related to status updates on Facebook. *Computers in Human Behavior*, *73*, 132-140. https://doi.org/10.1016/j.chb.2017.03.020

Eager, B., & Brunton, R. (2023). Prompting higher education towards AI-augmented teaching and learning practice. *Journal of University Teaching & Learning Practice*, *20*(5), Article 2. https://doi.org/10.53761/1.20.5.02

Elkins, S., Kochmar, E., Serban, I., & Cheung, J. C. (2023). How useful are educational questions generated by large language models? In N. Wang, G. Rebolledo-Mendez, V. Dimitrova, N. Matsuda, & O. C. Santos (Eds.), *Artificial intelligence in education* (pp. 536-542). Springer. https://doi.org/10.1007/978-3-031-36336-8_83

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies: Extending UTAUT2. *Interactive Technology and Smart Education*, *14*(4), 329-348. https://doi.org/10.1108/ITSE-06-2016-0015

Field, A. (2018). *Review of discovering statistics using IBM SPSS statistics* (5th ed.). SAGE.

Filipec, O., & Woithe, J. V. (2023). *Understanding the adoption perception and learning impact of ChatGPT in higher education* [Bachelor thesis, Jönköping University]. https://www.diva-portal.org/smash/get/diva2:1762617/FULLTEXT01.pdf

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39-50. https://doi.org/10.1177/002224378101800104

García de Blanes Sebastián, M., Sarmiento Guede, J. R., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, *13*, 993935. https://doi.org/10.3389/fpsyg.2022.993935

García-Méndez, S., de Arriba-Pérez, F., & Somoza-López, M. d. C. (2025). A review on the use of large language models as virtual tutors. *Science & Education*, *34*, 877-892. https://doi.org/10.1007/s11191-024-00530-2

Gibson, R. (2023, August 14). *10 ways artificial intelligence is transforming instructional design.* EDUCAUSE. https://er.educause.edu/articles/2023/8/10-ways-artificial-intelligence-is-transforming-instructional-design

Greene-Harper, R. T. (2023, April 11). *Revolutionizing instructional design: How artificial intelligence is transforming learning experiences.* LinkedIn. https://www.linkedin.com/pulse/revolutionizing-instructional-design-how-artificial-robin-t-/

Hadi, M. U., Qasem Al Tashi, Q., Qureshi, R., Shah, A., Muneer, A., Irfan, M., Zafar, A., Shaikh, M. B., Akhtar, N., Hassan, S. Z., Shoman, M., Wu, J., Mirjalili, S., & Shah, M. (2023). *A survey on large language models: Applications, challenges, limitations, and practical usage.* TechRxiv. https://doi.org/10.36227/techrxiv.23589741

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data Analysis* (6th ed.). Pearson Prentice Hall.

Harvey, E., Koenecke, A., & Kizilcec, R. F. (2025, April). "Don't forget the teachers": Towards an educator-centered understanding of harms from large language models in education. *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-19). Association for Computing Machinery. https://doi.org/10.1145/3706598.3713210

Hennekeuser, D., Vaziri, D. D., Golchinfar, D., Schreiber, D., & Stevens, G. (2025). Enlarged education – Exploring the use of generative AI to support lecturing in higher education. *International Journal of Artificial Intelligence in Education*, *35*, 1096-1128. https://doi.org/10.1007/s40593-024-00424-y

He-Yueya, J., Goodman, N. D., & Brunskill, E. (2024). Evaluating and optimizing educational content with large language model judgments. In B. Paaßen & C. D. Epp (Eds.), *Proceedings of the 17th International Conference on Educational Data Mining* (pp. 68-82). International Educational Data Mining Society.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Ivanov, S., & Soliman, M. (2023). Game of algorithms: ChatGPT implications for the future of tourism education and research. *Journal of Tourism Futures*, *9*(2), 214-221. https://doi.org/10.1108/JTF-02-2023-0038

Kaddour, J., Harris, J., Mozes, M., Bradley, H., Raileanu, R., & McHardy, R. (2023). *Challenges and applications of large language models.* PsyArXiv. https://doi.org/10.48550/arXiv.2307.10169

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasnec, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kereselidze, M. (2023). *The role of artificial intelligence in instructional design.* eLearning Industry. https://elearningindustry.com/role-of-artificial-intelligence-in-instructional-design

Kesmodel, U. S. (2018). Cross-sectional studies – what are they good for? *Acta obstetricia et gynecologica Scandinavica*, *97*(4), 388-393. https://doi.org/10.1111/aogs.13331

Koper, R. (2005). An introduction to learning design. In R. Koper & C. Tattersall (Eds.), *Learning design: A handbook on modelling and delivering networked education and training* (pp. 3-20). Springer. https://doi.org/10.1007/3-540-27360-3_1

Koper, R. (2006). Current research in learning design. *Journal of Educational Technology & Society*, *9*(1), 13-22. http://www.jstor.org/stable/jeductechsoci.9.1.13

Köpf, A., Kilcher, Y., von Rütte, D., Anagnostidis, S., Tam, Z. R., Stevens, K., Barhoum, A., Duc, N. M., Stanley, O., Nagyfi, R., Es, S., Suri, S., Glushkov, D., Dantuluri, A., Maguire, A., Schuhmann, C., Nguhen, H., & Mattick, A. (2023). *Open assistant conversations – Democratizing large language model alignment*. PsyArXiv. https://doi.org/10.48550/arXiv.2304.07327

Kozan, K., Hur, J., Kim, I., & Barrett, A. (2025). Instructional designers' integration of generative artificial intelligence into their professional practice. *Education Sciences*, *15*(9), 1133. https://doi.org/10.3390/educsci15091133

Krupp, L., Steinert, S., Kiefer-Emmanouilidis, M., Avila, K. E., Lukowicz, P., Kuhn, J., Kuchemann, S., & Karolus, J. (2023). Unreflected acceptance – Investigating the negative consequences of ChatGPT-Assisted problem solving in physics education. In F. Lorig, J. Tucker, A. D. Lindström, F. Dignum, P. Murukannaiah, A. Theodorou & P. Yolum (Eds.), *Hybrid human AI systems for the social good* (pp. 199-212). IOS Press. https://doi.org/10.3233/FAIA240195

Kumar, S., Gunn, A., Rose, R., Pollard, R., Johnson, M., & Ritzhaupt, A. (2024). The role of instructional designers in the integration of generative artificial intelligence in online and blended learning in higher education. *Online Learning*, *28*(3), 207-231. https://doi.org/10.24059/olj.v28i3.4501

Lanzi, P. L., & Loiacono, D. (2023). ChatGPT and other large language models as evolutionary engines for online interactive collaborative game design. *Proceedings of the Genetic and Evolutionary Computation Conference* (pp. 1383-1390). Association for Computing Machinery. https://doi.org/10.1145/3583131.3590351

Lee, J., Hicke, Y., Yu, R., Brooks, C., & Kizilcec, R. F. (2024). The life cycle of large language models in education: A framework for understanding sources of bias. *British Journal of Educational Technology*, *55*(5), 1982-2002. https://doi.org/10.1111/bjet.13505

Leiker, D., Finnigan, S., Gyllen, A. R., & Cukurova, M. (2023). *Prototyping the use of Large Language Models (LLMs) for adult learning content creation at scale.* PsyArXiv. https://doi.org/10.48550/arXiv.2306.01815

Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., He, H., Li, A., He, M., Liu, Z., Wu, Z., Zhao, L., Zhu, D., Li, X., Qiang, N., Shen, D., Liu, T., & Ge, B. (2023). Summary of ChatGPT-related research and perspective towards the future of large language models. *Meta-Radiology*, *1*(2), 100017. https://doi.org/10.1016/j.metrad.2023.100017

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of the CHI Conference on Human Factors in Computing Systems* (pp. 1-16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

Luo, T., Muljana, P. S., Ren, X., & Young, D. (2025). Exploring instructional designers' utilization and perspectives on generative AI tools: A mixed methods study. *Educational Technology Research & Development*, *73*, 741-766. https://doi.org/10.1007/s11423-024-10437-y

Malik, R., Abdi, D., Wang, R., & Demszky, D. (2025). Scaffolding middle school mathematics curricula with large language models. *British Journal of Educational Technology*, *56*(3), 999-1027. https://doi.org/10.1111/bjet.13571

Marr, B. (2024, March 19). *As AI expands, public trust seems to be falling.* Forbes. https://www.forbes.com/sites/bernardmarr/2024/03/19/is-the-public-losing-trust-in-ai/

McNeill, L., Uddin, M. M., Pei, M., & Regalado, L. (2025). Generative AI in instructional design: Adoption, benefits, and best practices. *The Journal of Applied Instructional Design. Special Issue: AI in Instructional Design*, Aubust, 108-134. https://doi.org/10.59668/2223.22720

Melián-González, S., Gutiérrez-Taño, D., & Bulchand-Gidumal, J. (2021). Predicting the intentions to use chatbots for travel and tourism. *Current Issues in Tourism*, *24*(2), 192-210. https://doi.org/10.1080/13683500.2019.1706457

Menon, D., & Shilpa, K. (2023). "Chatting with ChatGPT": Analyzing the factors influencing users' intention to use the OpenAI's ChatGPT using the UTAUT model. *Heliyon*, *9*(11) e20962. https://doi.org/10.1016/j.heliyon.2023.e20962

Meyer, J. G., Urbanowicz, R. J., Martin, P. C., O'Connor, K., Li, R., Peng, P.-C., Bright, T. J., Tatonetti, N., Won, K. J., Gonzalez-Hernandes, G., & Moore, J. H. (2023). ChatGPT and large language models in academia: Opportunities and challenges. *BioData Mining*, *16*, 20. https://doi.org/10.1186/s13040-023-00339-9

Moore, S., Tong, R., Singh, A., Liu, Z., Hu, X., Lu, Y., Liang, J., Cao, C., Khosravi, H., Denny, P., Brooks, C., & Stamper, J. (2023). Empowering education with LLMs – The next-gen interface and content generation. In N. Wang, G. Rebolledo-Mendez, V. Dimitrova, N. Matsuda, & O. C. Santos (Eds.), *Communications in Computer and Information Science* (pp. 32-37). Springer. https://doi0.org/100.1007/978-3-031-36336-8_4

Nguyen, Q., Huptych, M., & Rienties, B. (2018). Linking students' timing of engagement to learning design and academic performance. *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 141-150). Association for Computing Machinery. https://doi.org/10.1145/3170358.3170398

Niemi, H., Pea, R. D., & Lu, Y. (2023). Introduction to AI in learning: designing the future. In H. Niemi, R. D. Pea & Y. Lu (Eds.), *AI in learning: Designing the future* (pp. 1-15). Springer. https://doi.org/10.1007/978-3-031-09687-7_1

Pan, J. Z., Razniewski, S., Kalo, J. C., Singhania, S., Chen, J., Dietze, S., Jabeen, H., Omeliyanenko, J., Zhang, W., Lissandrini, M., Biswas, R., de Melo, G., Bonifati, A., Vakaj, E., Dragoni, M., & Graux, D. (2023). *Large language models and knowledge graphs: Opportunities and challenges.* PsyArXiv. https://doi.org/10.48550/arXiv.2308.06374

Pereira, E., Nsair, S., Pereira, L. R., & Grant, K. (2024). Constructive alignment in a graduate-level project management course: an innovative framework using large language models. *International Journal of Educational Technology in Higher Education, 21*, 25. https://doi.org/10.1186/s41239-024-00457-2

Pollard, R., & Kumar, S. (2022). Instructional designers in higher education: Roles, challenges, and supports. *The Journal of Applied Instructional Design*, *11*(1), 7-25. https://doi.org/100.59668/3540.5896

Reynolds, L., & McDonell, K. (2021). Prompt programming for large language models: Beyond the few-shot paradigm. *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (Article 314). Association for Computing Machinery. https://doi.org/10.1145/3411763.3451760

Russe, M. F., Reisert, M., Bamberg, F., & Rau, A. (2024). Improving the use of LLMs in radiology through prompt engineering: From precision prompts to zero-shot learning. *Rofo*, *196*(11), 1166-1170. https://doi.org/10.1055/a-2264-5631

Sağın, F. G., Özkaya, A. B., Tengiz, F., Geyik, Ö. G., & Geyik, C. (2024). Current evaluation and recommendations for the use of artificial intelligence tools in education. *Turkish Journal of Biochemistry*, *48*(6), 620-625. https://doi.org/10.1515/tjb-2023-0254

Salas-Pilco, S. Z., Xiao, K., & Hu, X. (2022). Artificial intelligence and learning analytics in teacher education: A systematic review. *Education Sciences*, *12*(8), 569. https://doi.org/10.3390/educsci12080569

Sallam, M. (2023). ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns. *Healthcare, 11*(6), 887. https://doi.org/10.3390/healthcare11060887

Schaper, N. (2024). Using ChatGPT to create constructively aligned assessment tasks and criteria in the context of higher education teaching. In S. Kadry (Ed.), *Artificial intelligence and education - Shaping the future of learning.* IntechOpen. https://doi.org/10.5772/intechopen.1005129

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*, Article 46. https://doi.org/10.1186/s41239-024-00478-x

Soodan, V., Rana, A., Jain, A., & Sharma, D. (2024). AI chatbot adoption in academia: Task fit, usefulness and collegial ties. *Journal of Information Technology Education. Innovations in Practice*, *23*, 1-27. https://doi.org/10.28945/5260

Spector, P. E. (2019). Do not cross me: Optimizing the use of cross-sectional designs. *Journal of Business and Psychology*, *34*(2), 125-137. https://doi.org/10.1007/s10869-018-09613-8

Sridhar, P., Doyle, A., Agarwal, A., Bogart, C., Savelka, J., & Sakr, M. (2023). *Harnessing LLMs in curricular design: Using GPT-4 to support authoring of learning objectives.* PsyArXiv. https://doi.org/10.48550/arXiv.2306.17459

Stone, T. (2023). *How generative AI will forever change the role of instructional designers.* Institute for Corporate Productivity. https://www.i4cp.com/productivity-blog/how-generative-ai-will-forever-change-the-role-of-instructional-designers

Strzelecki, A. (2023). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49,* 223-245. https://doi.org/10.1007/s10755-023-09686-1

Tam, D., Mascarenhas, A., Zhang, S., Kwan, S., Bansal, M., & Raffel, C. (2023). Evaluating the factual consistency of large language models through news summarization. *Findings of the Association for Computational Linguistics* (pp. 5220-5255). Association for Computational Linguistics. https://doi.org/10.18653/v1/2023.findings-acl.322

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, *2*, 53-55. https://doi.org/10.5116/ijme.4dfb.8dfd

Veletsianos, G. (2023, January 23). *AI, ChatGPT, instructional design, and prompt crafting.* https://www.veletsianos.com/2023/01/23/ai-chatgpt-and-instructional-design/

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Wang, S., Xu, T., Li, H., Zhang, C., Liang, J., Tang, J., Yu, P. S., & Wen, Q. (2024). *Large language models for education: A survey and outlook*. PsyArXiv. https://doi.org/10.48550/arXiv.2403.18105

Wang, Y., Zhong, W., Li, L., Mi, F., Zeng, X., Huang, W., Shang, L., Jiang, X., & Liu, Q. (2023). *Aligning large language models with human: A survey.* PsyArXiv. https://doi.org/10.48550/arXiv.2307.12966

Woo, B., Huynh, T., Tang, A., Bui, N., Nguyen, G., & Tam, W. (2024). Transforming nursing with large language models: From concept to practice. *European Journal of Cardiovascular Nursing*, *23*(5), 549-552. https://doi.org/10.1093/eurjcn/zvad120

Wu, T., Terry, M., & Cai, C. J. (2022, April). Ai chains: Transparent and controllable human-ai interaction by chaining large language model prompts. *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Article 385). Association for Computing Machinery. https://doi.org/10.1145/3491102.3517582

Yadav, G. (2023). *Scaling evidence-based instructional design expertise through large language models*. PsyArXiv. https://doi.org/10.48550/arXiv.2306.01006

Yang, F., & Stefaniak, J. E. (2025). An exploration of instructional designers' prioritizations for integrating ChatGPT in design practice. *Educational Technology Research and Development*, *73*, 2761-2784. https://doi.org/10.1007/s11423-025-10509-7

Zamfirescu-Pereira, J. D., Wong, R. Y., Hartmann, B., & Yang, Q. (2023, April). Why Johnny can't prompt: how non-AI experts try (and fail) to design LLM prompts. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Article 437). Association for Computing Machinery. https://doi.org/10.1145/3544548.3581388

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