NEW AGE OF TEACHING WITH PROFESSOR AI

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DECLARATION OF ORIGINALITY

I, Fatma Kasapoğlu, certify that

- I am the sole author of this thesis and that I have fully acknowledged and documented in my thesis all sources of ideas and words, including digital resources, which have been produced or published by another person or institution;
- this thesis contains no material that has been submitted or accepted for a degree or diploma in any other educational institution;
- this is a true copy of the thesis approved by my advisors and thesis committee at Boğaziçi University, including final revisions required by them.

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ABSTRACT

New Age of Teaching with Professor AI

Traditional teaching methods are evolving with Artificial Intelligence (AI) advancements. Higher education institutions (HEIs) must understand the students' acceptance of such technology to implement it successfully. This study aims to understand how students approach these new technologies and what the drivers are to determine the acceptance of AI-based tools usage in HEIs. We followed an empirical approach to assess the student acceptance. We used AI-equipped tools to prepare instructional materials, and generated course content in the form of an avatar teacher, then introduced the avatar teacher to the students in an in-class experiment. In the experiment, the avatar teacher lectured the students through AI-generated content. Afterward, a shared questionnaire with students helped evaluating how they approach the AI-based learning experience. Our analyses reveal that Performance Expectancy and Trust positively influence the Attitude of students with a strong mediating effect of Attitude on developing Behavioral Intention. At the same time, Social Influence is another strong indicator of developing Behavioral Intention. The findings indicate that students generally have a favorable view of Professor AI based on precise and reliable content delivery. At the same time, the non-human characteristics of the avatar and lack of interactivity set a drawback to student approval and highlight the improvement areas. Our study presents insights into AI-driven learning experiences and contributes to the literature on students' acceptance of AI in HEIs. The conclusions of this study serve as a roadmap for educators, developers, and policymakers who want to use AI tools in HEIs.

ÖZET

Profesör YZ ile Öğretimin Yeni Çağı

Geleneksel öğretim yöntemleri, Yapay Zeka (YZ) teknolojisindeki gelişmelerle değişmektedir. Yüksek öğrenim kurumlarının, bu teknolojileri uygulayabilmeleri için öğrencilerin YZ’a yönelik kabulünü anlamaları önemlidir. Bu çalışma, öğrencilerin YZ’a yaklaşımını ve YZ araçlarının kabul etkenlerini belirlemeyi amaçlamaktadır. Öğrenci kabulünü değerlendirmek için, çalışmamızda deneysel bir yaklaşım izledik. YZ donanımlı araçlar kullanarak eğitim materyalleri hazırladık, ve avatar öğretmen formunda ders içeriği oluşturduk. Ardından, sınıf içi bir deneyde avatar öğretmeni öğrencilere tanıttık. Deneyde, avatar öğretmen, YZ temelli içeriklerle öğrencilere ders anlattı. Sonrasında uygulanan anket çalışması ile, YZ tabanlı öğrenme deneyimine öğrencilerin nasıl yaklaştıkları değerlendirildi. Analizlerimiz, Performans Beklentisi ve Güven’in, Tutum üzerinde pozitif bir etkiye sahip olduğunu ve Tutum’un, Davranışsal Niyet’in gelişiminde güçlü bir aracılık etkisi gösterdiğini ortaya koymaktadır. Aynı zamanda Sosyal Etki, Davranışsal Niyet’in gelişiminde bir diğer güçlü göstergedir. Öğrenciler genel olarak Profesör YZ’nın etkili ve güvenilir içerik paylaşımı için olumlu bir bakış açısına sahip olduklarını gösterirken, avatarın insansı olmayan özellikleri ve etkileşim eksiklikleri eksiklik olarak görülmüş ve gelişim alanlarına işaret etmiştir. Çalışmamız YZ temelli öğrenme deneyimi hakkında içgörü sunmakta ve yüksek öğrenim kurumlarında YZ kullanımına ilişkin öğrenci kabulü açısından literatüre katkıda bulunmaktadır. Bu çalışmanın sonuçları, YZ araçlarını yükseköğretimde kullanmak isteyen eğitimcilere, geliştiricilere ve politika yapıcılara bir yol haritası niteliğindedir.

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CHAPTER 1

INTRODUCTION

Artificial Intelligence (AI) is bringing a new era to education, and traditional teaching methodologies are already changing. Educational institutions are incorporating AI more (Chen, Chen, & Lin, 2020). It is crucial to understand this new technology and its implications. AI is the computer and machine's ability to mimic humankind's cognitive skills and actions (Pinto Dos Santos et al., 2019). AI works as a system that accurately interprets external data, learns from the data, and uses the learnings to achieve specific goals and tasks with flexible adaptation (Kaplan & Haenlein, 2019). The historical evolution of AI spans several milestones. The foundational concepts of AI go back to the 1940s and 1950s (Kaplan & Haenlein, 2019). However, the idea of AI was firstly introduced in 1956 at the Dartmouth Conference with the objective to unite researchers to create a new research area to build machines able to simulate human intelligence (McCarthy, Minsky, Rochester, & Shannon, 2006). Significant improvements in this field evolved over the years as the development of the famous ELIZA program in the 1960s, the advent of expert systems in the 1980s, and the harness of AI started in the 2010s with the significant breakouts (Kaplan & Haenlein, 2019). During the 2010s, AI gained popularity with deep learning systems, machine learning, and data mining (Duan, Edwards, & Dwivedi, 2019).

Kaplan and Haenlein (2019) classify current AI systems into three categories as Analytical AI, Human-Inspired AI, and Humanized AI. Kaplan and Haenlein (2019) state that most current AI systems, such as image recognition and fraud detection, fall into the Analytical AI group, as the systems rely on cognitive intelligence, and learn from past experiences to make decisions. Human-inspired AI combines cognitive and emotional intelligence and enables systems to understand human emotions (Kaplan & Haenlein, 2019). Humanized AI systems integrate cognitive, emotional, and social intelligence with the aim of self-awareness and consciousness, yet such systems are not available, representing a future goal for AI technology (Kaplan & Haenlein, 2019).

AI has invaded numerous areas of life, including the educational sector and soon AI-enabled educational solutions will be common (Picciano, 2019). According to Chassignol, Khoroshavin, Klimova, and Bilyatdinova (2018), numerous aspects of the education, such as communication, teaching strategies, content creation, and student assessment, now use AI techniques. AI combines several technologies and methods, such as machine learning, natural language processing, data mining, neural networks, or algorithms (Baker & Smith, 2019). AI techniques are transforming education by enhancing personalized learning, improving assessment through intelligent systems, and enabling innovative tools and the advancements in AI complement traditional teaching methods (Chassignol et al., 2018). AI-enabled solutions promise that institutions will improve efficiency and effectiveness in teaching, personalization in learning, and efficiency in administrative procedures (Timms, 2016). AI-based tools can accelerate performing administrative tasks, such as grading and providing feedback, enabling institutions to tailor teaching materials according to student needs, and analyzing and creating course content (Chen et al., 2020). Customizable learning materials, performance monitoring, and prediction are all made possible by AI tools (Chen et al., 2020).

Higher Education Institutions (HEIs) play a pivotal role as they drive economic and social progress, foster research and innovation, and enhance global competitiveness

(Stonkiene, Matkeviciene, & Vaiginiene, 2016). HEIs contribute to a knowledgeable, innovative, and competitive society with their societal role of delivering a skilled working class (Stonkiene et al., 2016). Considering their societal position, HEIs must adapt to ensure they remain at the forefront of pedagogical evolution as AI revolutionizes education (Hannan & Liu, 2021).

HEIs are adopting advanced technologies such as AI, chatbots, and virtual reality, to enhance their teaching (Hannan & Liu, 2021). Implementing AI can enable HEIs to overcome several challenges in current educational settings. As traditional lecture-based methods involve limited interaction with students (Zhou, 2023), implementing AI can support HEIs to address the personalization needs of students to provide diversified and higher-quality education (Zhou, 2023). Student retention in HEIs is a major concern and AI can provide identification of at-risk students, enabling institutions to provide tailored interventions (Shiao et al., 2023). Additionally, AI provides automation on administrative tasks, such as automated grading, providing feedback, student performance monitoring, course scheduling, and data management (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019). By automating these time-consuming and resource-intensive tasks, AI allows instructors to focus more on teaching and enhancing the overall educational experience (Zawacki-Richter et al., 2019).

Avatar-assisted educational environments are another aspect of AI implementation in HEIs. Avatars are computer-animated figures in virtual interfaces with features like speech, gesture, and expressions (Adamo-Villani & Dib, 2016). In the context of HEIs, virtual environments can contribute to subject-based higher competence (Kumar et al., 2023). Avatars can be virtual tutors and an Avatar-based lecture approach can enable institutions to promote student engagement, provide clear content, and improve learning outcomes (Adamo-Villani & Dib, 2016). Avatar usage in education can also enhance remote teaching in HEIs as an alternative to common remote learning environments (Thanyadit, Heintz, & Law, 2023). Additionally, avatars can promote inclusive education for students with disabilities, with features such as gestures and expressions (De Martino et al., 2017).

Integrating AI solutions in education attracts researchers, yet there is a need for more research in this field (Ouyang, Zheng, & Jiao, 2022). According to Chen et al. (2020), there has been a significant increase in the interest in AI and education relationships. Despite the growing interest in the literature on AI usage in education, most reviews focus on the general application of AI in education, not specifically in higher education (Ouyang et al., 2022). Ouyang et al. (2022) state that there still needs to be more studies in the literature that examine the purpose and effects of AI techniques in higher education and emphasize the need for more empirical studies to investigate AI usage in HEIs. The limited literature on AI arises from the recent adoption of AI, lack of comprehensive reviews covering empirical effects, focusing on AI applications in general education, or focusing on specific contexts of AI resulting in a lack of holistic view of AI applications (Ouyang et al., 2022).

In this study, we tested AI-generated and avatar-narrated course contents with volunteer students to address the gap in the literature regarding higher education-specific research content (Ouyang et al., 2022), AI-based intelligent tutoring applications (Zawacki-Richter et al., 2019), and limited evaluation of acceptance with an empirical study in HEIs. We seek to understand how students approach fully AI-derived teaching content and the key drivers to increase acceptance. Notably, this study aims to evaluate acceptance factors among HEI towards AI-based education tools from the student perspective with an empirical approach.

This study contributes to a deeper understanding of student acceptance towards AI-based teaching tools. Our study offers a comprehensive empirical investigation into the factors determining AI acceptance of students in the context of HEIs. By delving into the student perspective, we aim to provide insights into the factors influencing this transition from traditional educational paradigms to innovative methodologies. Generating AI-based course content and avatar teacher serves as a step-by-step paradigm of how avatars and AI can be integrated into educational environments. Our study provides insights on creating AI-based course content and implementing narrator avatars. The utilization of avatar teachers can save instructors time, allowing them to focus on research tasks, enhance student engagement, and provide students with customized learning paths and supplemental resources. Additionally, this study serves as a foundation for future studies and provides guidance and recommendations for educators, developers, and policymakers to navigate the transformative journey of adopting AI-driven approaches effectively. By addressing both theoretical and practical aspects, we aim to guidance for the design and implementation of AI-based Avatar tools by providing student perceptions to maximize benefits and minimize challenges. Overall, with this study, we aim to contribute to the ongoing technological evolution of HEIs.

This thesis comprises the following chapters: Chapter 1 introduces the study overview. Chapter 2 presents the literature review for the AI application areas in higher education purposes, Avatar usage for teaching purposes in higher education institutes, and the acceptance of AI in education. We explained the theoretical model and the study's hypotheses in Chapter 3. Chapter 4 explains the methodology applied in the study in detail. We reported the analyses and the study findings in Chapter 5. Discussion of the results shared in Chapter 6. In Chapter 7, we shared the study's conclusion. Lastly, we discussed the study's limitations and the opportunities for future studies in Chapter 8.

CHAPTER 2

LITERATURE REVIEW

2.1 Artificial intelligence and education in HEIs

From an educational standpoint, AI has the potential to significantly impact teaching and learning in higher education as a field that has emerged over the past 30 years (Zawacki-Richter et al., 2019). Popenici and Kerr (2017) define AI as computer systems that can perform human-like functions like self-correction, learning, adapting, synthesizing, and using data for complicated processing tasks. The main objective of AI is to create artificial systems that can understand, simulate, and reproduce human intelligence and cognitive processes (Jia, Sun, & Looi, 2024). Higher Education Institutions (HEIs) started integrating AI-based educational solutions into their systems (Hannan & Liu, 2021). Hannan and Liu (2021) highlight those advanced technologies like AI, can unlock new competitive advantages for HEIs.

AI's features such as providing automation, prediction and personalization opens new opportunities in education (George & Wooden, 2023). AI can be used in education to predict learning status, performance, or satisfaction, for resource recommendation, automatic assessment purposes, and to improve the learning experience (Ouyang et al., 2022). Utilizing AI tools can provide improved prediction accuracy, provide personalized recommendations, and enhance student performance and engagement (Ouyang et al., 2022). Table 1 displays AI implications to the education in HEIs.

Table 1. AI Usage Areas and Implications

AI usage areas	Implications
Managing student learning	Learning analytics (Deo et al., 2020), Student profiling (Raffaghelli et al., 2022)
Predicting	Academic performance (Zhu et al., 2023), Stundent dropout and retention (Shiao et al., 2023)
Assessment and evaluation	Automated assessment (Vittorini et al., 2021), Automated feedback (Zheng et al., 2023)
AI assistants	Virtual assistants (Lahav et al., 2020), Chatbot assistance (Kuhail et al., 2023)
Intelligent tutoring systems	Adaptive and personalized learning (Yu et al., 2017)

AI can provide HEIs opportunities, such as learning analytics, strengthen methodologies using technology and big data, and build student performance management systems that uncover success elements and retention factors and evaluate the effect of assignments and tests on student satisfaction (Deo et al., 2020). Zhu, Liu, Chen, Chen, & Li (2023) argue that learning behavior impairments are highlighted as one of the main reasons for academic failure. AI can be used to anticipate student behavior by evaluating data on academic performance, predicting dropout risks, identifying at-risk students, and providing tailored interventions to enhance learning outcomes (Shiao et al., 2023). Early Warning Systems (EWS) play a crucial role in improving student retention in education by using AI to predict performance and identify students at risk of dropping out (Raffaghelli, Rodríguez, Guerrero-Roldán, & Bañeres, 2022). By analyzing learning analytics, these systems help educators monitor student progress, provide personalized support, and intervene when necessary (Raffaghelli et al., 2022). AI performs dropout prediction as a part of EWS. Dropout occurs when learners discontinue participation before completion (Bañeres, Rodríguez-González, Guerrero-Roldán, & Cortadas, 2023). AI models like Dropout Risk-Level

Identification and predictive tools display significant reduction in dropout rates (Bañeres et al., 2023). Such systems analyze student data, forecast risks, and offer early interventions, helping teachers provide timely academic support and improve retention rates (Shiao et al., 2023). Score prediction can avoid student learning performance risks by determining important factors that affect student scores, enabling educators to obtain insights into students' performance, and supporting better and timely teaching decisions (Zhu et al., 2023).

Artificial intelligence can automate grading to help teachers and give students instant feedback, improving the grading process and student performance (Vittorini, Menini, & Tonelli, 2021). Automatic assessment systems can assess students' answers based on predefined criteria while providing timesaving for students and educators, ensuring grading consistency and real-time feedback (Grivokostopoulou, Perikos, & Hatzilygeroudis, 2017). Automatic Assessment Systems can be desirable for education as they provide efficiency, consistency, and objectivity in evaluation performance while providing timesaving in the manual evaluation process; also, their scalability feature offers the opportunity to handle many students (Grivokostopoulou et al., 2017).

Among all the application areas of AI in education, personalization commonly stands out as an important benefit offered by AI tools. Individualized learning preferences are an important aspect, and the integration of AI into education emerges as a promising opportunity for HEIs to address limitations in traditional methods in this regard (George & Wooden, 2023). As each student has their own learning pace and learning preferences, current teaching methodologies in traditional teaching cannot meet the requirements when it comes to teaching on an individualized level (Xiao & Yi, 2021). HEIs can address the needs of students on individualized level by utilizing AI

(Chassignol et al., 2018). Li and Wong (2021) describe personalized learning as teaching each student based on their knowledge, skills, and capabilities. Implementing AI-based personalized learning platforms to the teaching methodologies enables educators to create individualized learning experiences and provides students to improved learning and teaching conditions, enhanced cognitive abilities while fostering problem-solving skills (Zhou, 2023). To achieve personalization in education, AI-based customized training models and tailored training plans should be employed by colleges and universities (Xiao & Yi, 2021).

Zheng et al. (2023) argue that feedback has an immense positive impact on learning outcomes by encouraging coregulated behaviors, improving group performance, and facilitating collaborative knowledge development. The learner can arrange performance by engaging with the more experienced and skilled counterparty by initiating the feedback (Taskiran & Goksel, 2022). AI technologies like deep learning and personalized recommendation systems were promising for empowering feedback processes (Zheng et al., 2023). Automated feedback systems provide an affordable way to help students since they provide timely and limitless feedback, which motivates students to keep going (Taskiran & Goksel, 2022). Taking care of common problems, automated feedback technologies can also let teachers free up their time to concentrate on other tasks (Taskiran & Goksel, 2022).

AI also provides assistance in a variety of forms, including intelligent agents, virtual assistants, and intelligent instructors (Crompton & Burke, 2023). AI assistants' main responsibilities include responding to inquiries from students, giving tailored feedback, facilitating self-assessment, and assisting students with their academic assignments (Crompton & Burke, 2023). As intelligent agents, Chatbots serve as teachable agents for problem-solving, motivational agents for encouragement, peer agents for on-demand assistance, and teaching agents for tutorials, discussions, and assessments (Kuhail, Alturki, Alramlawi, & Alhejori, 2023). Chatbots are software tools that communicate with users using natural, conversational text or voice and various fields integrate chatbots, including education (Smutny & Schreiberova, 2020). Empirical studies highlight their effectiveness, noting increased perceived usefulness and usability, though user satisfaction varies (Kuhail et al., 2023). When integrated into intelligent tutoring systems, chatbots boost engagement and learner understanding, particularly in negotiation tasks (Kerly, Hall, & Bull, 2007). Although they cannot yet wholly replace human teachers, chatbots can be helpful as teaching assistants who answer routine questions, facilitate customized learning, and improve instruction in subjects like distance learning and foreign languages (Pérez, Daradoumis, & Puig, 2020).

Exploring Machine Learning and AI technologies to elevate teaching systems and traditional methods can lead to better student educational outcomes (Qi, Liu, Kumar, & Prathik, 2022). Large Language Models are another promising AI solution for education in the context of machine learning and deep learning. A large language model is an advanced type of AI model that aims to understand and generate human language (Zhang, Hofmann, Plößl, & Gläser-Zikuda, 2024). These models can perform text classification, sentiment analysis, and question answering based on deep learning technologies (Zhang et al., 2024). Zhang et al. (2024) suggest that leveraging pre-trained language models can improve educational processes such as assessment strategies for reflective writing.

ChatGPT, a prominent generative model, offers tailored, conversational support for tasks like research, case analysis, and creative thinking (Chaudhry, Sarwary, El

Refae, & Chabchoub, 2023). The tool used a pre-trained model to generate human-like responses by using a large corpus of data scanned from the internet, and it innovatively creates texts based on user prompts within seconds (Crawford, Cowling, & Allen, 2023). ChatGPT holds several opportunities for educational reform, such as personalized learning as it can provide tailored content and feedback, promotes interactive learning through real-time response, and improves accessibility as it can provide content in multiple formats like text, voice, and video (Rawas, 2024). Additionally, using ChatGPT for teaching purposes can enable instructors to streamline tasks like grading and support them to generate consistent course materials (Rawas, 2024).

Despite the benefits of such technology, its implementation requires cautious planning and a clear understanding of its opportunities and challenges (Rawas, 2024). Over-reliance on AI solutions risks undermining critical thinking and self-reliance (Crawford et al., 2023). Reliance on AI solutions like generative pre-trained transformer models for educational assignments might diminish critical thinking, ethical use, and cheating (Chaudhry et al., 2023). For the successful implementation of this technology in education, there is a need for support and guidance from institutions to guide students in navigating the use of such tools to establish a clear envision to relevantly benefit from AI-generated content in the learning experience (Eager & Brunton, 2023).

2.2 AI-enabled tools and learning environments in HEIs

In recent years, new learning environments like Distance Learning or Massive Open Online Courses (MOOCs) have come into life for HEIs. MOOCs provide an opportunity to reach many learners and make university courses available to students at a nominal cost to institutions (Yu, Miao, Leung, & White, 2017). It changes the landscape of higher education by providing large-scale learning (Yu et al., 2017). MOOCs make university courses available to thousands of students cost-efficiently, challenging traditional educational models as they allow institutions to reach many students without time and space limitations (Yu et al., 2017). However, scaling up class sizes while maintaining quality poses challenges, and issues such as limited communication, high dropout rates, and lack of hands-on experience are noted in current MOOC offerings (Yu et al., 2017). Institutions can overcome these educational limitations by integrating AI into MOOCs (Yu et al., 2017). AI tools can assist in addressing growing requests for individualized support and much larger class sizes in open and remote learning environments (Taskiran & Goksel, 2022).

Researchers can analyze vast amounts of information covering instructional behavior, learning, emotion, motivation, and social interaction with the aid of AI (Muthmainnah, Ibna Seraj, Oteir, 2022). AI enables researchers to gain deeper insights into the advantages of personalized learning environments by utilizing data from students' experiences (Muthmainnah et al., 2022). AI's sophisticated algorithms efficiently handle the complicated structure of high-density classrooms, responding to both usual instructing flaws and students' differing personal requirements (Muthmainnah et al., 2022). By implementing AI-based learning tools in teaching processes, instructors can enhance student engagement and improve student learning by implementing a flipped-blended mode in traditional learning settings (Schroeder, Hubertz, Van Campenhout, & Johnson, 2022). Instructors can also benefit from AI-based teaching platforms that enable them to optimize teaching content (Schroeder et al., 2022). Additionally, the collected data can help to detect pain points in the student learning journey so instructors can address challenges accordingly (Schroeder et al., 2022).

Virtual learning environments (VLE) deploy AI, as it can contribute to subject-based higher competence while creating a positive student perception (Kumar et al., 2023). Virtual reality integration in education for the specialization in professions, such as biology and medical science, can positively impacts students' learning experience and enjoyment by improving focus, confidence, and relevance to the learning content (Kumar et al., 2023). Additionally, AI supports collaborative learning in VLEs where students work together to achieve common educational objectives (Hirata, 2023). Hirata (2023) highlights how AI in VLEs reduce anxiety and improve confidence in communication compared to traditional methods, fostering an inclusive and engaging atmosphere.

2.3 The role of avatar in education for teaching purposes

Johnson and Lester (2016) argue that integrating animated interface agent technologies into intelligent learning environments can promote better learning outcomes. Such technologies promote natural and humane interactions between systems and users (Johnson & Lester, 2016). A pedagogical agent is an autonomous character in learning environments that serves as a virtual tutor, coach, or teammate, and facilitates instruction through organic, human-like interactions with expressing emotions (Johnson & Lester, 2016). Using pedagogical agents in education can promote effectiveness as it can enhance learning compared to agent-free environments, especially in science and math courses rather than humanities (Schroeder, Adesope, & Gilbert, 2013). By lowering cognitive search demands and fostering a socially engaging learning environment, these agents, which use verbal and non-verbal cues like gestures and looks, can increase engagement (Dunsworth & Atkinson, 2007). Pedagogical agents are more impactful when speaking than using text (Schroeder et al., 2013). Animated educational agents in multimedia learning can enhance also retention through the image and embodied agent effects (Dunsworth & Atkinson, 2007).

Virtual agents, often known as avatars, are computer-animated figures that perform gestures, speech, and facial expressions in interactive computer interfaces (Adamo-Villani & Dib, 2016). Avatar-based lecture approach can help educational institutions enhance student engagement, improve student understanding, increase student motivation, provide explicit content, create interactive learning opportunities, and encourage learning experiences (Adamo-Villani & Dib, 2016). Avatar's gestures can be instrumental in clarifying educational content, providing personality, and engaging with students through interactive learning (Adamo-Villani & Dib, 2016). Students' motivation and comprehension can increase with the avatar's perception of interesting, enjoyable, and engaging lectures (Adamo-Villani & Dib, 2016). Avatar-based lectures can also increase student competency in technical courses (Adamo-Villani & Dib, 2016).

Avatar agents can be integrated into virtual education settings as tutors, mimicking teacher presence in 3D setting and allow students to focus on both the materials and the teacher simultaneously (Thanyadit et al., 2023). Such AI-enabled educational settings can automatically create body language, movements, gestures and gaze of the real teacher (Thanyadit et al., 2023). Additionally AI techniques in avatar-led virtual environments can be utilized for distance learning to capture student attendance by eye movements and allow instructors to analyze student attention (Thanyadit et al., 2023). Virtual agents are also beneficial in education by providing students with counseling and provide valuable support for students and assist in decision-making by engaging in conversations (Lahav, Talis, Cinamon, & Rizzo, 2020). Virtual counseling can provide users anonymity, flexibility, and accessibility by conveniently scheduling consultation meetings, still human interaction preference over avatar counsel can be challenging (Lahav et al., 2020). It is important to understand user preferences to explore the shifting landscape of education with avatar usage. Daniels and Lee (2022) state that avatar instructors in virtual settings can create appreciation in students by providing flexibility and availability to re-watch virtual learning; distraction and lack of hands-on experience are challenges students to adapt such technology. Elements of avatar instructors like voice tone, conciseness and visualizations promote student interest, however, pacing of speech and unpleasant feeling to interact can cause student dislike (Daniels & Lee, 2022).

2.4 Acceptance of AI in education

User acceptance is important to investigate for implementation of AI applications into education successfully. This study aims to guide institutions to understand student acceptance factors. AI is becoming a growing trend in education, and the scientific community are interested in improving this practice, however little is known about the acceptance these technologies as educational agents (Sánchez-Prieto, Cruz-Benito, Therón, & García-Peñalvo, 2020). The willingness of the parties involved in education is a crucial component that ensures the success of any process involving technological innovation and the creation of acceptance models to examine the conditions that influence such acceptance might, therefore, yield crucial data for the creation of new projects in this field (Sánchez-Prieto et al., 2020). The future direction of AI-powered learning environments hinges not only on the ongoing development of technology, but also on users' willingness to accept, believe in, and adjust to these revolutionary developments (Algerafi, Zhou, Alfadda, & Wijaya, 2023). Several theories in the literature based on sociology and psychology explain user acceptance of new technologies like AI-based products and the factors affecting their intentions (Chatterjee & Bhattacharjee, 2020). We will discuss prominent technology acceptance models and theories in the following sub-sections.

2.4.1 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action is a psychological model developed by Martin Fishbein and Icek Ajzen in 1975, and its goal is to predict and reason human behavior by focusing on the subject's intention to perform a behavior (Sheppard, Hartwick, & Warshaw, 1988). According to TRA, two main factors influence the behavioral intentions of individuals: Attitudes as determined by the beliefs about the outcomes of the behavior and the evaluations of these outcomes, and Subjective Norms as perceived social pressures to perform a behavior and influenced by individual's beliefs and motivations to comply with others' behaviors (Sheppard et al., 1988). Despite the theory's predictive power on consumers' behavioral intentions on a broad range of consumer products, TRA does not include consumers' personality traits, demographic factors, or social roles that influence user behavior, and it is challenging to eliminate subjective norms that affect behavioral intention (Olushola & Abiola, 2017). In accordance with TRA, Figure 1 displays that an individual's behavioral intention (BI) to carry out a specific behavior is defined by their attitude (A) and subjective norm (SN) for the behavior in question (Fishbein & Ajzen, 1975).

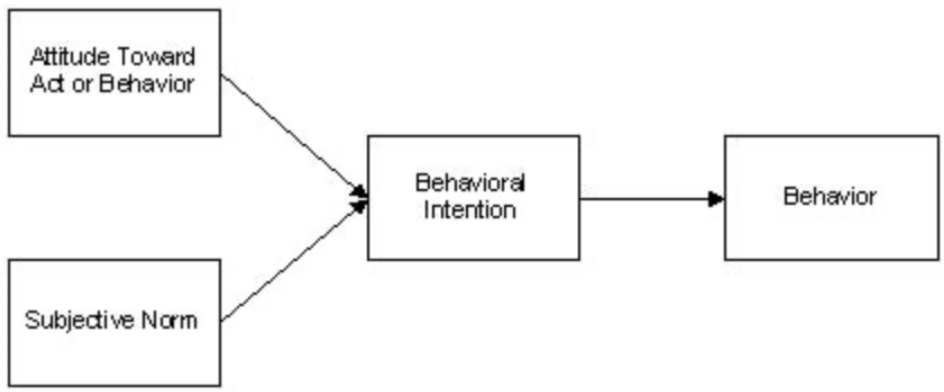

Figure 1. Theory of Reasoned Action (TRA)

2.4.2 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is derived from TRA, modified explicitly for modeling user acceptance of information systems by Fred D. Davis in 1986 (Davis, Bagozzi, & Warshaw, 1989). Its goal is to provide a general explanation of the factors affecting computer acceptance that can be applied to a broad range of user computing technologies in a theoretically proven way (Davis et al., 1989). Two primary constructs of TAM are Perceived Usefulness (PU), which is the degree to which a person believes that using the system would improve their performance, and Perceived Ease of Use (PEU), which is the degree to which a person believes that using a system would cause no effort (Davis et al., 1989). TAM hypothesizes that these two ideas influence the users' attitudes regarding the system, impacting their behavioral intentions to use the system and, eventually, how they use it (Davis et al., 1989). Figure 2 displays the hypothesized relations between constructs according to TAM. According to the paradigm, behavioral intention is directly impacted by perceived usefulness, whereas behavioral intention is influenced by perceived ease of use both directly and indirectly through perceived usefulness (Davis et al., 1989).

One major challenge to using the Technology Acceptance Model (TAM) outside of the workplace is that its basic assumptions do not adequately consider the variety of user task environments (Moon & Kim, 2001). TAM's absence of a task-specific emphasis indicates that more research into the complex effects of technology and usage contexts is necessary to improve its external validity (Dishaw & Strong, 1999).

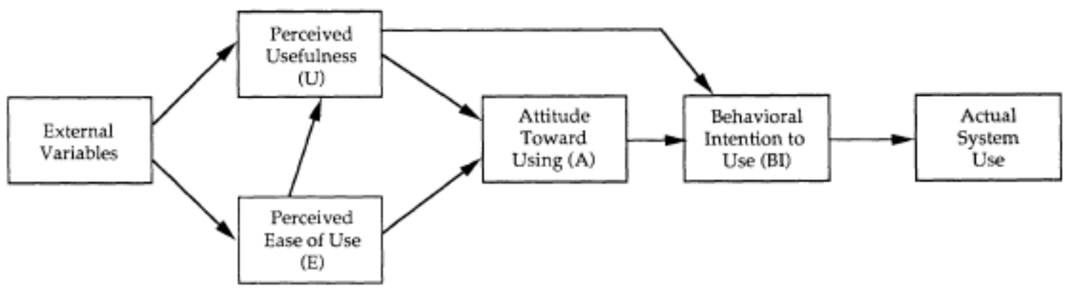

Figure 2. Technology Acceptance Model (TAM)

2.4.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

Among other theories, the Unified Theory of Acceptance and Use of Technology (UTAUT) outperforms to explain the variance related to behavior intention, compared to the other eight models and theories (Venkatesh, Morris, Davis, & Davis, 2003). Venkatesh et al. (2003) derived UTAUT by reviewing existing models, which are the theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Motivational Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TBP (C-TAM-TPB), Model of PC Utilization (MCPU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT) as they examined the core constructs and determinants of intention and usage in each model. They conducted empirical comparisons of the eight other models using data collected from four organizations for six months and measured user intentions to use information technology (Venkatesh et al., 2003). Based on the conceptual and empirical similarities among the eight models, Venkatesh et al. (2003) formulated a unified model. Figure 3 displays the model with relationships of UTAUT. UTAUT has four main determinants of intention and usage: performance expectancy, effort expectancy, social influence, and facilitating conditions, and these are combined with four moderators: age, gender, experience, and voluntariness (Venkatesh et al., 2003). As empirically validated by Venkatesh et al. (2003), UTAUT combines elements from other theories as a comprehensive framework to understand user acceptance and usage of new technology with a significant explanatory power of the variance in user intention and behavior compared to its predecessor models and constitutes a valuable tool for the researchers.

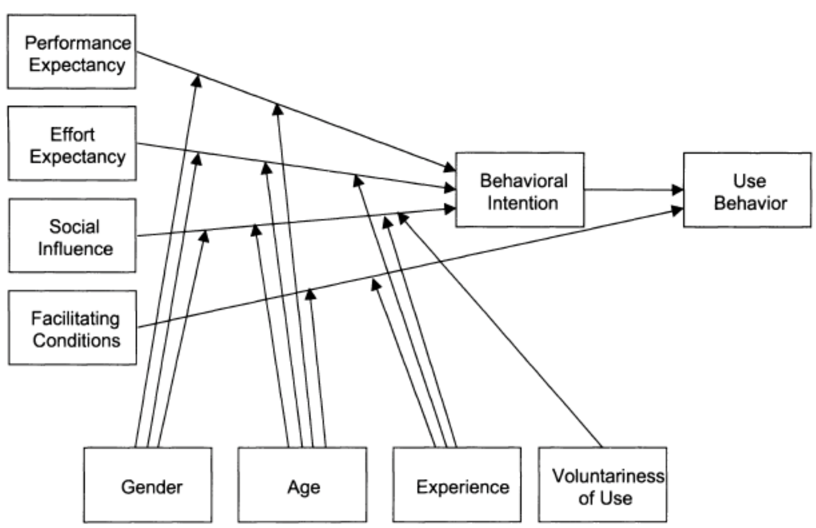

Figure 3. Unified Theory of Acceptance and Use of Technology (UTAUT)

CHAPTER 3

THEORETICAL MODEL AND HYPOTHESES

As UTAUT combines the other eight models and creates a comprehensive model to understand user intention with a higher explanatory power (Venkatesh et al., 2003), we used UTAUT as a foundation for our study. We used four exogenous constructs of UTAUT, which are Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social Influence (SI); however, due to unmeaningful results in our analysis, we dropped EE, which we will discuss later in the limitations of our study. Additionally, moderators such as gender, age, voluntariness, and experience of UTAUT were excluded in our model to interpret how only exogenous constructs impact behavioral intentions, in respect to the samples of our study were all college students with similar backgrounds and age groups (Chatterjee & Bhattacharjee, 2020). In contrast, UTAUT moderators consider participants from different backgrounds and organizations (Chen & Hwang, 2019). Moreover, according to the study conducted by Marchewka, Liu & Kostiwa (2007), gender and age did not moderate online learning systems in higher education.

Additionally to the core constructs of UTAUT, our model considers the mediating effect of Attitude (ATT). ATT was integrated into the original TAM (Davis et al., 1989), and as ATT is differentiated from Behavioral Intention (BI) (Vermeir & Verbeke, 2006). We included ATT in our model in accordance with prior studies (Chatterjee & Bhattacharjee, 2020; Wu, Wu, & Chang, 2016) as mediating construct to develop BI.

Moreover, we included Trust (TR) in our model. In educational technology, trust is evaluated as a driver for adoption (Hamidi & Chavoshi, 2018). Trust can be explained as the degree to the user that the new technology is credible, reliable, and secure based on their beliefs (Bilquise, Ibrahim, & Salhieh, 2023). Users are more likely to use the new technology if their beliefs comply with it and they are optimistic about accepting it (Fernandes & Oliveira, 2021).

Lastly, we included Stickiness to Human Teacher (ST) in our model as a moderating construct, as students' intention to use AI-based instructors can be reduced by their preferences for traditional learning forms of human teachers (Pillai, Sivathanu, & Kaushik., 2023). As a relatively new technology, some participants may resist learning from a digital avatar and prefer to learn with traditional teaching methods (Pillai et al., 2023). In this study, we aim to investigate users' behavior intentions and participants' stickiness to learning from human teachers. Since stickiness moderates the relation between attitude and behavioral intention, we added ST as a moderating variable to our model.

In summary, with the developed model, we aimed to evaluate student acceptance determinants of AI-based learning content instructed by an avatar teacher. In the following part, our constructs will be introduced in detail.

3.1 Model constructs and hypothesis formation

Performance Expectancy (PE):

According to UTAUT, PE is the degree to which a user believes that using the new technology would help them attain sizable gains in their job performance (Venkatesh et al., 2003). PE is constructed based initially on the Perceived Usefulness (PU) construct of TAM, and similar to PU, it has a powerful positive impact on Attitude (ATT) (Chatterjee & Bhattacharjee, 2020). By our model, we define PE as the degree to which students believe that using AI-based education solutions will help them achieve better academic performance, and the following hypothesis developed:

H1: Performance Expectancy (PE) positively associated with Attitude (ATT).

Social Influence (SI):

Social Influence (SI) could be linked to a desire to improve one's reputation and social position as well as a more objective requirement for trustworthy information sources (Chiyangwa & (Trish) Alexander, 2016). According to previous studies, users can rely on others' judgments and acquaintances in their preferences (Shin, 2010). Therefore, we employ SI as the influence of social factors, such as peers, teachers, and parents, on students' decisions to use AI in education, and the following hypothesis developed:

H2: Social Influence (SI) positively associated with Behavioral Intention (BI).

Social factors, such as peers, educators, and parents, students' perceptions of the availability of necessary infrastructure and support for the effective use of AI-based educational solutions, and their positive attitudes toward this new instructional technology influence their intention to use AI-based educational solutions.

Facilitating Conditions (FC):

Facilitating Conditions (FC) construct is the degree to which a person thinks that the necessary technological and related infrastructure is efficiently available to enable the use of the new system (Venkatesh et al., 2003) and the positive influence of FC on BI recognized in the literature (Howard, Restrepo, & Chang, 2017; Lancelot Miltgen, Popovič, & Oliveira, 2013). Therefore, we define FC in our model as the extent to which students perceive that the necessary infrastructure and support are in place for the effective use of AI-based education solutions, and the following hypothesis developed:

H3: Facilitating Conditions (FC) positively associated with Behavioral Intention (BI).

Trust (TR):

Building user trust is crucial for the expansion and success of adoption, and insufficient trust is a significant barrier to the acceptance of the technology (Hamidi & Chavoshi, 2018). In the absence of trust, users can be deterred from utilizing the new technology to its maximum capacity when they lack trust in it (Lee & Choi, 2017). According to prior studies, trust is directly related to attitude (Roy, Babakerkhell, Mukherjee, & Funilkul, 2022). In our model, we use TR as the extent to which an individual believes the technology is credible, reliable, and secure and following the hypothesis developed:

H4: Trust (TR) positively associated with Attitude (ATT).

Students' beliefs that AI-based educational solutions can enhance their academic performance and their trust in the technology contribute to their positive attitudes toward new technology.

Attitude (ATT):

Davis et al. (1989) assert that a person's attitude toward utilizing a system determines their behavioral intention (BI) in the Technology Acceptance Model (TAM) and ATT is demonstrated in prior studies as it serves as an influential mediating variable in the interpretation of behavioral intention (BI) (Chatterjee & Bhattacharjee, 2020; Cox, 2012) and Roy et al. (2022) reports that attitude towards technology adoption has an impact on behavior intention. We defied ATT in our model as the degree to which a student favors or dislikes the new teaching technology, and the following hypothesis developed:

H5: Attitude (ATT) positively associated with Behavioral Intention (BI).

Behavioral Intention (BI):

Davis et al. (1989) define BI as a measure of the strength of a person's intention to perform a behavior influenced by the ATT, which originated in TRA. In our model, BI is defined as students' intention to use AI-based education solutions influenced by ATT, SI, and FC.

Stickiness to Human Teacher (ST):

Stickiness to Human Teacher (ST) is the power of traditional approaches to maintain people's preference towards them over new technologies (Pillai et al., 2023). As students are acquainted with the traditional settings where they are used to being instructed by human teachers, ST can be a negative moderating factor in user behavior (Pillai et al., 2023). In our study, ST was defined as the power of student preference to learn from human teachers traditionally rather than using avatars, and the following hypothesis was developed accordingly:

H6: Stickiness to Human Teacher (ST) moderates the relationship between Attitude (ATT) and Behavioral Intention (BI).

Students' preference for learning from traditional human teachers overusing avatars serves as a moderating factor in the relationship between their attitudes toward new learning technology and their intention to use this new educational solution.

3.2 Proposed theoretical model

Figure 4 exhibits the final theoretical model to explore factors influencing students' intention to accept AI-based education solutions. Performance Expectancy (PE) is defined as the belief that using AI will enhance academic performance, with the hypothesis that PE positively influences Attitude (ATT) (H1). Social Influence (SI) refers to the impact of peers, teachers, and parents on students' decisions to use AI, and it is hypothesized to positively influence Behavioral Intention (BI) (H2). Facilitating Conditions (FC) involve the availability of infrastructure and support for using AI-based solutions, with the hypothesis suggesting FC positively influences Behavioral Intention (BI) (H3). Trust (TR) refers to students' belief in the credibility and security of AI technology, and it is hypothesized that TR positively influences Attitude (ATT) (H4). Attitude (ATT) is defined as students' positive or negative view of AI, with the hypothesis that ATT positively influences Behavioral Intention (BI) with a mediating role (H5). Behavioral Intention (BI) is students' intention to use AI, influenced by ATT, SI, and FC. Finally, Stickiness to Human Teacher (ST) is the preference for traditional teaching methods over AI, and it is hypothesized that ST moderates the relationship between Attitude (ATT) and Behavioral Intention (BI) (H6).

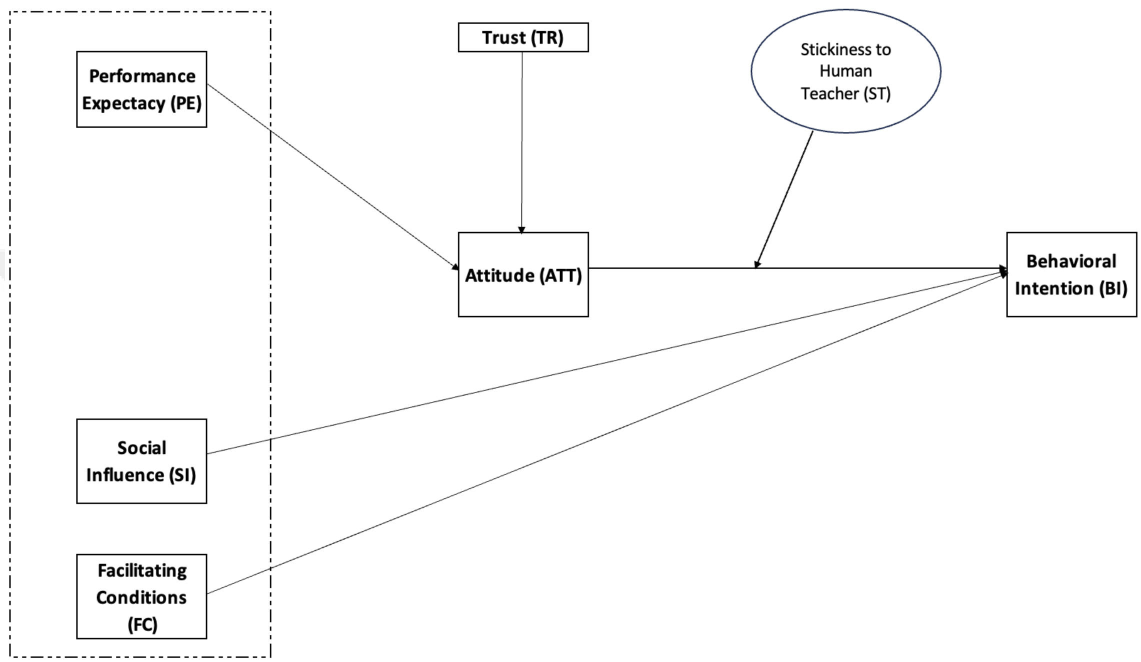

Figure 4. Proposed theoretical model

CHAPTER 4

METHODOLOGY

This chapter describes the technical details of course content generation and validation, together with the experiment and questionnaire design based on the theoretical model used to evaluate student acceptance. In this study, we aimed to create course contents for four different courses using only Artificial Intelligence-enabled tools. Generated course content is embodied and narrated via avatar, which is also generated by AI instruments. To set an example for HEIs, we created the course material in this study entirely with AI-based resources. This study also acts as a guide for laying out the stages involved in implementing AI in the educational setting.

After the course contents were developed, an avatar teacher introduced the prepared materials to the volunteer student groups during one-hour class sessions in the experimental phase. We share the ethics committee approval to run the experiment in the Appendix A. The experiment phase took place in a mid-sized education institution in Turkiye. This implementation measures the factors influencing students' acceptance of avatar-based new learning technologies. Following their interaction with the new technology, we administered a post-test to evaluate their perceptions based on our theoretical model. The results of the experiment were analyzed to understand students' acceptance factors and their relations to guide higher education institutions for the AI-based tools used in teaching purposes.

4.1 Course content generation and validation

As our experiment would take place in classroom environments, firstly, the content topics were agreed upon with the instructors of selected courses. Before the content generation, course content details were discussed with the course instructors to set clear objectives for creating compatible content through AI. Total of four courses were selected as a mix of technical and non-technical courses for the course content generation and the experiment practice with the alignment of the course instructors.

To generate the instructive content for the selected topics, we used ChatGPT as the intermediary AI tool. Based on the agreed-upon content and the objectives expected from the content, ChatGPT was utilized, and the content for the selected topics was generated through prompting. In the prompting, we prompted ChatGPT to generate the course content based on the agreed-upon content expectation and the sub-sections to be covered for each chapter by the course instructors.

> Example prompting:
>
> "I want to generate a course content for university students in presentation format. The course is about "data representation". I will give you a topic for each slide of presentation and I want you to generate me a slide content about that topic, following to the slide content share me a narrative that explains that slide. I want the slide contents comprehensive, highlighting important aspects. I want the slide narratives in detailed explanation with good examples to make audience understand."

The prompting for the content generation was an iterative process as we prompted ChatGPT for each slide to be used in the presentation format, and each response of ChatGPT was checked and prompting altered if an adjustment or explanation was required based on the response of AI. For each slide of the course content, we prompted ChatGPT to generate a corresponding narrative to explain the content to the students, which the Avatar instructor uses in the following steps. Detailed examples for the prompting and outputs of ChatGPT shared in the Appendix B.

As the experiment will take place in a lecture within the lecture time for each content, we aimed for the content duration to be 20 to 30 minutes. Two subject-matter experts in the project team and the course instructors evaluated the first step's outputs. If any part of the course material did not meet their evaluation criteria, the first step was re-performed based on the feedback received.

4.2 Narrator avatar generation and validation

We transferred the validated content and content script into the narrator avatar, using Synthesia as an AI tool. Synthesia is used for creating realistic video content featuring virtual avatars. It uses advanced deep-learning techniques to generate avatar-based video content based on the script provided by users. Synthesia offers expressive avatars which can adjust facial expressions, voice and demeanor based on the narrative. Based on our subscription plan, we had access to five expressive avatars which are three females and two males. We preferred a female avatar as the individuals can be more likely to connect to female avatars as they perceived as more approachable and authentic (Liu & Hao, 2024). Figure 5 exhibits the avatar content editing screen in the Synthesia.

Figure 5. Narrator avatar generation

Two subject-matter experts evaluated the final product (narrator Avatar) similarly in section 4.1. If the avatar did not meet their criteria, the third step was re-performed based on the feedback received and the content edited. Figure 6 displays a glimpse of a final course content as avatar teacher.

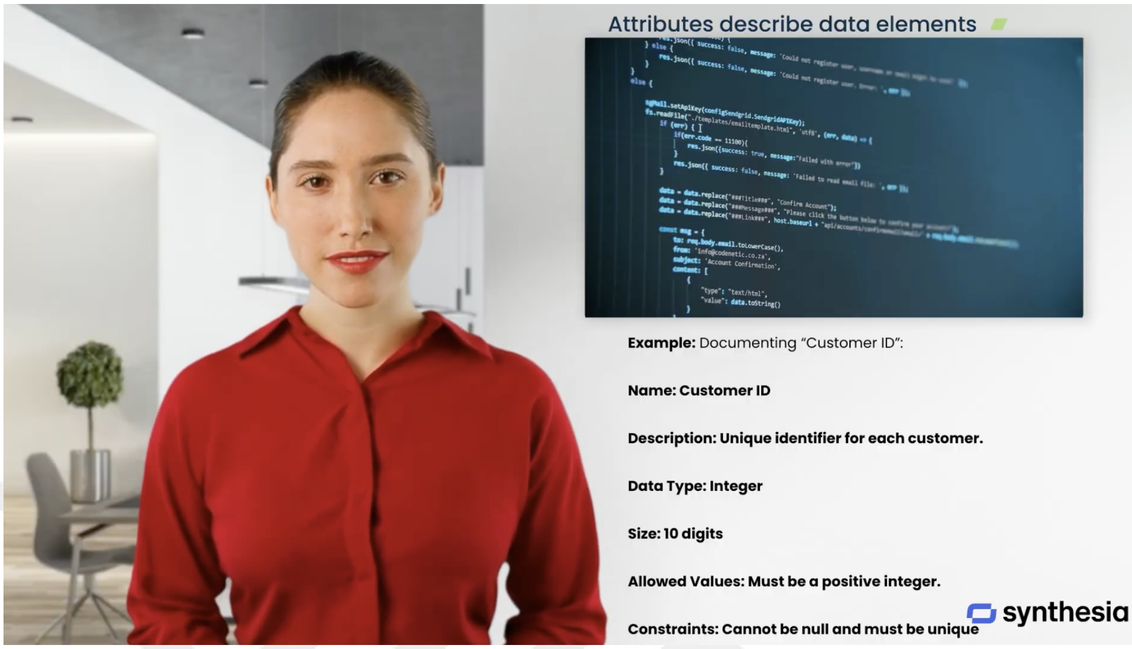

Figure 6. Final course content as Professor AI

4.3 Experiment design

After generating four course content for each selected lecture as avatar teacher, course instructors informed enrolled students prior the experiment. The experimental phase took place in each course during a pre-announced lecture time in the Fall 2024 semester. Participation in the study was voluntary, and students could leave the experiment at any time if they wanted to. Before the experiment, students were informed about the aim of the study and the experiment phase. Afterward, we shared the consent forms with the students. In the teaching session, students watched avatar teacher as a video content in the classroom environment. After the session we shared the link and QR code to the digital questionnaire with the participants.

For the experiment, we applied a multi-phased approach. For the quantitative analysis, a questionnaire was applied based on the theoretical model with multiple choice questions asked based on 5-point Likert-scale questions ((1) Strongly Disagree; (2) Disagree; (3) Neither Agree nor Disagree; (4) Agree; (5) Strongly Agree), following optional three open-ended questions asked to gain more insight about the student perception towards to avatar teacher. We conducted the data collection anonymously, and no student identification information was collected.

4.4 Questionnaire details

In our study, to measure the acceptance of the students to use AI-based solutions in education, we build our model based on the Unified Theory of Acceptance and Use of Technology (UTAUT). The theoretical model is supported by content-related supporting constructs and moderators. The survey-questions are developed in accordance to the theoretical model and based on the literature for each construct corresponding questions included in the questionnaire. PE and SI scales were adapted from Venkatesh et al. (2003), FC from Chatterjee and Bhattacharjee (2020), TR from Lee and Choi (2017), ATT from Li (2023), ST from Pillai et al., (2023), and BI from Venkatesh, Thong, and Xu (2012). The details of the scales to measure the constructs shared construct in the Appendix C.

We prepared the questionnaire by using SurveyMonkey, an online survey platform for creating and distributing surveys. Figure 7 illustrates the survey instrument. The questionnaire consists of four parts. The first part is the statement of the study's objectives. In the second part, the demographic information of the participants was collected with two questions as "year in the university", and "gender".

We asked the participants to choose their grade with a multiple-choice question as "Freshman," "Sophomore," "Junior," "Senior," or "Master Student." The gender was also asked multiple-choice as “Female,” “Male,” “Nonbinary,” and “Preferred not to say.” In the third part, 29 multiple choice questions were asked. Moreover, participants were allowed to choose one of the choices. The questions were derived from various sources, as referenced in Appendix C.

Figure 7. Questionnaire screens

Lastly, we asked three optional open-ended questions to participants as follows:

What are the points that you liked?

What are the points that you do not like?

What are the points that can be improved?

We asked these questions as a complementary source to understand student sentiment for avatar teacher, allowing us to detect areas of strength and areas for improvement in the avatar teacher experience. All survey data was collected anonymously; we did not request any identifying information from the participants. Only the demographic information on gender and class information was collected, in addition to their reflections on the experiment to evaluate the acceptance constructs. Anonymously collected information is kept in the password-protected cloud environment by the ownership of the project coordinator.

4.5 In-class experiment with volunteer participants

The generated course content was introduced in the classroom to the volunteer students as announced before the experiment by the instructor of each course. From the four sessions, total of 195 students participated to the experiment. The duration of the lecture led by AI varied between 20 to 30 minutes for each course. Afterward, questionnaire access was given to the participants to capture their reflections about the learning session. To prevent any knowledge inequality between volunteer and non-volunteer students and to avoid students' course performance being affected by the experiment, the same content is instructed by the instructors in the next learning session.

CHAPTER 5

ANALYSES AND FINDINGS

We employed the Partial Least Squares Structural Equation Modeling (PLS-SEM) method to evaluate the theoretical model. Partial Least Squares Structural Equation Modeling (PLS-SEM) is a statistical technique that analyzes complex relationships between observed and latent variables (Haenlein & Kaplan, 2004). As a causal modeling technique, PLS-SEM aims to maximize the variance explained by the dependent latent components (Hair, Ringle, & Sarstedt, 2011). PLS-SEM gives priority to theory creation and prediction, in contrast to covariance-based SEM, which concentrates on replicating the theoretical covariance matrix, and it is beneficial when the goal of the study is to make predictions rather than to confirm structural correlations (Hair et al., 2011). PLS-SEM is very useful for theory creation, exploratory research, and scenarios where the main objective is to predict important target constructs or identify important "driver" constructs. It works with considerably smaller and much larger samples, is more robust with fewer identification problems than SEM, and easily integrates formative and reflective aspects (Hair et al., 2011). We chose PLS-SEM for analysis in this study as a powerful and effective tool for researchers since it is adaptable to small sample sizes and does not necessitate distributional assumptions (Haenlein & Kaplan, 2004).

Usually, PLS-SEM evaluation is conducted in two steps, with separate assessments of the measurement and structural models to ensure reliability and validity. In PLS-SEM, the structural model, also known as the inner model, shows the unidirectional paths between latent constructs, permitting only recursive relationships where paths flow in a single direction. In contrast, the measurement model, known as the outer model, represents the unidirectional predictive relationships between latent constructs and their associated observed indicators (Hair et al., 2011).

From the four in-class experiments, a total of 195 volunteer participants completed the questionnaire, and the data collected from questionnaires was extracted directly from SurveyMonkey in Excel format. The "10-Times Rule" has been used to determine the sample size. According to the 10-Times Rule, widely accepted in the PLS-SEM literature, the minimum sample size should be equal to either (1) ten times the number of formative indicators used to measure a single variable or (2) ten times the most significant number of structural paths directed at a particular latent construct in the structural model (Hair et al., 2011). In this context, considering the dependent, independent, mediator, and moderator variables of our theoretical model used as the basis for our study, a minimum sample size of 70 participants is estimated based on a total of 7 variables. Although 70 participants were deemed sufficient according to this rule, we reached a higher number of participants, 195.

We used WarpPLS software to conduct the analyses. The questionnaire responses for each survey were combined directly into one text file and uploaded to WarpPLS to conduct the analysis. Moreover, we conducted a thematic analysis of the responses to the open-ended questions.

5.1 Participant demographics

The descriptive analysis was conducted based on the demographic characteristics of the participants. Table 2 shows the demographic characteristics of the participants. About 56% were males, 39% were females, 4% were nonbinary, and 1% preferred not to share gender information. Based on their year of university education, 31% of the participants were freshmen, 22% were sophomores, 16% were juniors, 24% were seniors, and 7% were master students.

Table 2. Descriptive Analysis

Item	Category	Sample Size	%
Gender	Male	109	56%
	Female	76	39%
	Nonbinary	8	4%
	Prefer not to say	2	1%
	Total	195	100%
Class	First Year (Freshman)	61	31%
	Second Year (Sophomore)	43	22%
	Third Year (Junior)	31	16%
	Fourth Year (Senior)	47	24%
	Master Student	13	7%
	Total	195	100%

5.2 Measurement model analysis

We conducted confirmatory factor analysis before the theoretical model's fitness and validity checks. In line with structural equation modeling, confirmatory factor analysis (CFA) is a statistical method used to verify whether observed variables accurately reflect underlying latent components (Ahire & Devaraj, 2001). In addition to accounting for measurement error and testing the relevance of factor loadings, it outlines the relationships between variables and evaluates model fit (Ahire & Devaraj, 2001).

Additionally, CFA guarantees the unidimensionality of scales, provides flexibility in correlations, and validates measurement tools, improving construct validity and reliability in research (Ahire & Devaraj, 2001). Table 3 indicates our model CFA results. Factor loadings should be at least greater than 0.5 (Hair, Blake, Babin, & Tatham, 2006), and Table 3 indicates that the factor loadings of our model are above thresholds and displays and the cross-loadings low as it ensures unidimensionality.

To ensure validity, a test's internal consistency should be assessed before it is used for research or analysis (Tavakol & Dennick, 2011). The degree to which every item in a test measures the same idea or construct is known as internal consistency, and which is related to the interrelatedness of the test's components (Tavakol & Dennick, 2011). Cronbach’s Alpha is commonly used to measure the internal consistency of the items (Ahire & Devaraj, 2001). For most research purposes, Cronbach's Alpha of 0.70 or above is generally thought of as acceptable; however, in exploratory or early-stage studies, slightly lower value as 0.60 accepted as threshold (Ahire & Devaraj, 2001).

Like Cronbach’s Alpha, Composite Reliability (CR) is an indicator of a construct’s internal consistency, but more suitable for SEM (Hair et al., 2011). In contrary to Cronbach’s Alpha, CR does not assume that all indicators are equally reliable and prioritizes indicators according to their reliability during model estimation (Hair et al., 2011). Composite reliability (CR) scores should be at least 0.7 to be considered satisfactory (Pallant, 2013).

Average Variances Extracted (AVE) is used in the assessment of the discriminant validity of a measurement instrument, as a measure associated with a latent variable (Kock, 2015c). It shows how much variance a concept typically collects from its indicators in comparison to how much variance is caused by measurement error (Hair et al., 2011). AVE of 0.50 indicates that the construct explains more than half of the variance of its indicators and sets an acceptable threshold for AVE value (F. Hair Jr, Sarstedt, Hopkins, & G. Kuppelwieser, 2014).

Table 3 displays the reliability and validity figures for the theoretical model based on the constructs. Most constructs exhibit strong factor loadings, with values generally above the recommended threshold of 0.70, ensuring reliable indicators. Cronbach's alpha and CR values are predominantly above 0.70, indicating high internal consistency, though ST’s Cronbach’s alpha (0.656) is slightly below 0.7 and displays marginal acceptable value. AVE values of the constructs exceed 0.50, confirming sufficient validity. Overall, the model demonstrates good reliability, and the validity of each construct seems sufficient for Cronbach’s Alpha, Composite Reliability, and AVE values.

Table 3. Confirmatory Factor Analysis and Reliability Measures

	PE	SI	FC	ATT	TR	BI	ST	ST*ATT	Cronbach's Alpha	Composite Reliability	AVE
PE1	0.889	0.007	0.029	0.116	0.044	0.025	0.025	-0.017	0.912	0.938	0.791
PE2	0.885	-0.021	-0.008	-0.062	-0.012	-0.026	-0.083	-0.071			
PE3	0.867	-0.035	-0.006	-0.061	-0.064	0.027	0.007	0.047			
PE4	0.916	0.047	-0.014	0.006	0.029	-0.024	0.049	0.041			
SI1	0.119	0.788	-0.224	-0.056	0.063	-0.161	-0.040	-0.017	0.749	0.842	0.574
SI2	-0.064	0.796	-0.210	-0.126	0.036	0.068	-0.043	-0.021			
SI3	-0.016	0.805	0.092	0.011	-0.059	0.087	0.060	0.031			
SI4	-0.047	0.628	0.428	0.215	-0.049	0.003	0.026	0.008			
FC1	0.096	-0.352	0.762	0.176	0.093	0.017	0.041	0.078	0.760	0.847	0.581
FC2	-0.110	-0.030	0.770	0.037	-0.103	0.264	0.055	-0.016			
FC3	0.077	-0.012	0.741	-0.103	0.162	-0.182	0.031	-0.004			
FC4	-0.059	0.386	0.777	-0.110	-0.143	-0.105	-0.124	-0.056			
ATT1	-0.188	0.010	-0.055	0.893	-0.100	0.050	0.052	-0.017	0.910	0.937	0.788
ATT2	-0.118	0.123	-0.073	0.903	0.082	-0.114	-0.036	0.033			
ATT3	0.084	-0.113	0.026	0.894	-0.025	0.034	-0.041	0.023			
ATT4	0.231	-0.022	0.108	0.860	0.043	0.033	0.026	-0.041			
TR1	0.106	0.130	0.051	0.284	0.690	-0.181	-0.036	-0.048	0.837	0.892	0.675
TR2	0.001	-0.074	0.020	-0.268	0.844	0.263	-0.005	0.014			
TR3	-0.081	0.094	-0.010	-0.108	0.869	-0.065	-0.066	0.015			
TR4	-0.004	-0.126	-0.050	0.142	0.870	-0.048	0.099	0.009			
BI1	0.006	0.010	-0.016	-0.009	0.039	0.910	0.030	-0.037	0.908	0.942	0.845
BI2	-0.040	0.082	-0.013	-0.007	-0.024	0.924	0.037	0.071			
BI3	0.035	-0.092	0.029	0.016	-0.015	0.923	-0.066	-0.035			
ST1	0.133	0.001	-0.039	0.158	-0.109	-0.209	0.721	-0.103	0.656	0.814	0.593
ST2	-0.089	0.037	-0.074	0.006	0.009	0.117	0.784	0.098			
ST3	-0.033	-0.037	0.107	-0.147	0.089	0.074	0.803	-0.003			
ST*ATT	0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	1.000	1.000	1.000	1.000

According to Hair et al. (2006), discriminant validity explains how one construct differs from other constructions, and to determine discriminant validity, verifying correlations using the square root of AVE for that construct can be performed. When the AVE persistently exceeds the squared correlation of the other components, discriminant validity is supported (Hair et al., 2006).

Table 4 displays the correlations among constructs with the square roots of AVEs to assess discriminant validity as highlighted diagonally. The diagonal values represent the square roots of AVEs, which are all higher than the corresponding inter-construct correlations. This indicates good discriminant validity, as each construct shares more variance with its indicators than with other constructs. Overall, the table demonstrates that the constructs exhibit appropriate discriminant validity.

Table 4. Variable Correlations

	PE	SI	FC	ATT	TR	BI	ST	ST*ATT
PE	0.889							
SI	0.638	0.758						
FC	0.217	0.380	0.763					
ATT	0.641	0.609	0.186	0.888				
TR	0.442	0.472	0.244	0.482	0.822			
BI	0.735	0.674	0.197	0.716	0.514	0.919		
ST	0.061	0.103	0.169	0.001	0.208	0.132	0.770	
ST*ATT	-0.028	0.071	0.069	0.051	-0.072	0.035	-0.194	1.000

Additionally, the assessment of Common Method Bias (CMB) is a crucial step in guaranteeing the validity of Results in PLS-SEM. Standard method bias is a phenomenon that arises from the measuring technique used in the study rather than from the causal relationship between the latent variables in the model under investigation (Kock, 2015a). For example, the instructions at the top of a questionnaire may sway the responses of several respondents in the same general direction, resulting in some common variation among the indicators sharing a certain amount of common variation, leading to inflated path coefficients and potentially misleading results (Kock, 2015a). In this study, we employed the complete collinearity variance inflation factor (VIF) approach to evaluate the potential for CMB, as proposed by Kock and Lynn (2012). This method examines multicollinearity across all latent constructs in the model, as VIF values can indicate the degree of shared variance caused by a standard method (Kock & Lynn, 2012). Kock and Lynn (2022) state that the threshold for a VIF value of 3.3 and higher values would indicate collinearity.

Table 5 displays the full collinearity VIF values of the constructs in the theoretical model. All VIF values are below the commonly accepted threshold of 3.3, which indicates that the data does not suffer from critical levels of multicollinearity that could arise from a standard method bias. Based on this, observed relationships among constructs are not artificially inflated by a shared measurement method in our model, which indicates that multicollinearity is not a concern in this study.

Table 5. Full Collinearity VIFs

PE	SI	FC	ATT	TR	BI	ST	ST*ATT
2.496	2.350	1.225	2.374	1.529	3.212	1.144	1.080

5.3 Structural model analysis

We applied structural model analysis to test the hypotheses developed based on the theoretical model and determine the relationships between constructs of the model, following the evaluation of the measurement model. In PLS-SEM, structural model analysis entails assessing the connections (paths) among latent constructs, and the level and significance of the path coefficients are important evaluation criteria for the structural model (Hair et al., 2011). Path coefficient estimation is a crucial component in empirical studies using PLS-SEM since it is the foundation for hypothesis testing (Kock, 2018). Each path coefficient indicates a hypothesis, which is checked by computing a p-value linked to the path coefficient (Kock, 2018). The appropriate hypothesis is presumed to be accepted if a p-value falls below a specific threshold (Kock, 2018), and the threshold is generally used as 0.05 (Kock, 2015b).

Table 6 shows the path coefficients and p-values for the relationships within the theoretical model and represents the effects of the variables on each other. Path coefficients and p-values were employed to assess the power and statistical significance of the developed hypotheses for the relationships between constructs of the theoretical model proposed. The final model displaying the PLS-SEM results for path coefficients and p-values shared in Appendix D.

Table 6. Path Coefficients and P-Values

Hypothesis	Constructs	Path Coefficient β	p-values
H1	PE -> ATT	0.532	< 0.001
H2	SI -> BI	0.377	< 0.001
H3	FC -> BI	-0.030	0.338
H4	TR -> ATT	0.252	< 0.001
H5	ATT -> BI	0.491	< 0.001
H6	ST*ATT -> BI	0.027	0.351

5.4 Analysis of the hypotheses

H1: Performance Expectancy (PE) positively influences Attitude (ATT).

According to the structural model analysis, this hypothesis is strongly supported, displaying performance expectancy significantly and positively influencing attitude. A path coefficient of $\beta = 0.532$ for the relationships between constructs suggests a strong relationship, indicating that the student's belief that using AI-based education solutions will help them achieve better academic performance positively influences their attitude toward adopting Professor AI, and the p-value as < 0.001 displays a statistically significant relationship.

H2: Social Influence (SI) positively influences Behavioral Intention (BI).

The results show that social influence (SI) significantly affects behavioral intention (BI). A moderate path coefficient of $\beta = 0.377$ suggests that Social factors such as peers, educators, and parents, students' perceptions of the availability of necessary infrastructure and support for the effective use of AI-based educational solutions, and their positive attitudes toward this new instructional technology influence their intention to use AI-based educational solutions. The p-value as < 0.001 displays a statistically significant relationship. This finding highlights the importance of considering social and cultural contexts when designing AI-based instruments for HEIs.

H3: Facilitating Conditions (FC) positively influence Behavioral Intention (BI).

The outcomes of the theoretical model's analysis do not support this hypothesis, as the relationship between Facilitating Conditions and Behavioral Intention is not statistically significant. The weak negative path coefficient of $\beta = -0.030$ and p-value = 0.338 highlight that facilitating conditions, such as the availability of resources or technical support, do not directly drive behavioral intention in this context.

H4: Trust (TR) positively influences Attitude (ATT).

The relationship between trust and attitude is significant, with a moderate positive path coefficient of $\beta = 0.252$ and a p-value of < 0.001, which displays a statistically significant relationship. This finding displays that students' trust in Professor AI contributes to their positive attitudes toward acceptance, as trust plays an important role in contexts involving new or unfamiliar technologies.

H5: Attitude (ATT) positively influences Behavioral Intention (BI).

Attitude strongly influences behavioral intention, as evidenced by a path coefficient of $\beta = 0.491$ and a p-value of < 0.001, which displays a statistically significant relationship. This significant relationship reinforces the idea that students with a favorable attitude toward using Professor AI are more likely to intend to use it.

H6: Stickiness to Human Teacher (ST) moderates the relationship between Attitude (ATT) and Behavioral Intention (BI).

According to the model analysis results, the moderating effect of Stickiness to Human Teacher on the relationship between Attitude and Behavioral Intention is not significant. The weak path coefficient $\beta = 0.027$ and high p-value = 0.351 suggest that Stickiness to Human Teacher does not meaningfully moderate the influence of Attitude on Behavioral Intention.

Additionally, we tested the impact of gender and the class on BI by using them as independent variables. The relationships between gender-BI ($\beta = 0.067$ and high p-value = 0.173) and class-BI ($\beta = -0.056$ and high p-value = 0.216) revealed as statistically insignificant.

5.5 Thematic analysis

We applied Thematic Analysis to evaluate the responses collected from the open-ended questions. Thematic Analysis is a method applied to quantitative data to identify, analyze, and report patterns (referred to as themes) through data (Braun & Clarke, 2006). Thematic analysis is characterized by its flexibility and can be used to produce descriptive, explanatory, or critical insights (Lochmiller, 2021). It enables researchers to organize and describe data sets flexibly as they can be applied to varying theoretical frameworks in qualitative research (Braun & Clarke, 2006).

Thematic Analysis involves several phases, including familiarizing oneself with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. This method helps summarize key features of large data sets, highlighting similarities and differences and generating insights that can inform policy development. It includes several steps, such as getting acquainted with the data, creating preliminary codes, looking for themes, evaluating themes, identifying and labeling themes, and creating the final report (Braun & Clarke, 2006). Identified themes represent the essence of the data and provide a comprehensive understanding of the participants' perspectives and experiences (Lochmiller, 2021).

Thematic Analysis was performed for the three open-ended questions asked of the students to determine their likes, dislikes, and opinions about the improvement areas. The Analysis was conducted through Microsoft Excel following the analysis steps (Braun & Clarke, 2006) as follows:

-Familiarizing with the data

-Generating initial codes related to each statement

-Searching for themes within codes

-Reviewing themes

-Defining and naming themes

-Summarizing and reporting the outcomes of the Analysis

Thematic Analysis can be applied through software or manually. For analysis purposes, we used Microsoft Excel; we performed coding manually due to the relatively small and manageable sample size and to avoid focusing on software rather than the data itself, as the software tools can be overwhelming to get familiar with and the instructions complex to follow (Saldaña, 2013).

In the analysis, we evaluated each question separately. Firstly, we read corresponding student responses for each question to familiarize ourselves with the data. Then, we generated corresponding codes in an Excel file for each statement shared by students. In a statement, more than one sentiment could be shared; thus, multiple codes for a statement are evaluated and included in the coding part. Once we generated all the codes, we evaluated the unique codes to group the codes and gain insight into the appearing themes within the codes. Following that, we reviewed and defined the themes. In the following section, we share the results of the analysis.

Q1: What are the points that you liked?

For this question, 117 students responded among 195, and based on the responses, eight themes were concluded. Table 7 shares a percentage split of the appearing codes within corresponding themes. Consequently, the most appealing themes are explained as follows:

Table 7. Themes for the Liked Points of Professor AI

Theme	%
Clarity and Communication	29%
Efficiency and Learning Support	18%
Accuracy and Reliability	16%
Content and Structure	16%
User Experience	12%
Human-like Qualities	5%
Miscellaneous/Other	4%
Technology and Innovation	2%

Clarity and Communication:

The responses consistently highlighted Professor AI's clarity and fluency of speech as strengths. Clarity of pronunciation, smoothness of speech, and intelligibility were key factors in effective learning. The AI's ability to explain concepts clearly and understandably made the learning process easier for students, according to codes such as "clear and frequent lectures," "clear speaking," "effective use of language," "Good pronunciation and diction," and "Easy to understand."

Example quotes

> "The lecture was clear and frequent. AI is a better and faster learning objective than physical lectures. I am planning to use AI technology much more than in-class lectures."
>
> "The way that Professor AI was very clear and understandable. The way she points all the subjects out about the class was great."
>
> "I liked how clear the AI professor spoke and the flow of the lesson was clear."

Efficiency and Learning Support:

The AI professor was perceived as efficient, allowing students to learn faster and focus on the key points. Students valued how quickly the material was delivered, often faster than traditional teaching methods. Efficiency was emphasized in terms of saving time and providing a direct, focused learning experience without unnecessary elaboration, according to the codes "Focus on essential information," "Faster learning," and "Summarization."

Example quotes

“Thanks to AI we can learn lots of things faster than professors' lessons.”

“Professor AI teaches us about only the necessary topic and it is quicker than our human professor.”

“The fact that it can provide any information needed with the right resources provided as a tutor quickly. A tutor spends years developing the knowledge to teach, AI can produce classes to low - budget students.”

Accuracy and Reliability:

The AI was praised for providing accurate, reliable, and precise information. According to the codes appearing as “Reliable and convincing information,” “Accurate information,” and “Conciseness,” the AI focused on delivering concise, relevant material, ensuring that students were not overwhelmed by unnecessary information.

Example quotes

“All of the information shared throughout the lesson was reliable and convincing.”

“The information overall is very true and the info flow is also very great.”

“I liked that the AI teacher explained only the necessary information shortly and clearly and finished the topic quickly.

Content and Structure:

Responses often mentioned how the content was structured well and provided real value to students based on the appearing codes like “Effective use of visual effects,” “Systematic structure,” and “Fluent and efficient presentation.”

Example quotes

> “The AI professor effectively uses visual effects during the course”
>
> “The whole structure of the lecture was very clean and accurate.”
>
> “The way of presenting the information was good.”

User Experience:

The Professor AI was viewed as very user-friendly. Students noted that the interface was simple, and the fact that they could access it anytime made learning more convenient. Accessibility was a significant benefit from the user experience standpoint, as students appreciated learning on their own time without being limited by traditional class schedules. Appearing codes as such “Accessibility for private classes,” “Ease of access,” and “Availability”:

Example quotes

> “The accessibility would be amazing for private classes.”
>
> “It is easy to take a class from Professor Ai as it is computer-based.”
>
> “Real human professors are not always available for teaching. Instead of manual search on the internet, lectures created by this AI could be seen as a way more reliable and effective way of learning when there is need.”

Q2: What are the points that you don't like?

For this question, 136 students responded among 195, and based on the responses, ten themes were concluded. Table 8 shares a percentage split of the appearing codes within corresponding themes. Consequently, the most appealing themes are explained as follows:

Table 8. Themes for the Disliked Points of Professor AI

Theme	%
Content Delivery	33%
Emotion & Expression	20%
Interaction & Engagement	18%
Pace & Clarity	13%
Visuals & Presentation	5%
Human vs. AI Preference	4%
Not distinctive than available materials	2%
Accuracy and Reliability	1%
Miscellaneous/Other	1%
Customizability & Adaptability	1%

Content Delivery:

The content of the lectures was often seen as basic or generic, with many students feeling that the material covered was available elsewhere on the internet.

The lack of in-depth analysis, real-life examples, and contextual richness made Professor AI's teaching feel less dynamic than that of a human instructor. According to the codes "long duration," "boring," and "monotonous," they are indicated as boring and hard to pay attention to.

Example quotes

> "The duration of the video was so long. I would prefer a video that has brief and effective points only."
>
> "The lecture was boring because AI only talks about the things that I could find easily on the internet"
>
> "The speaking style of AI professors is monotonous and does not include interaction. I felt like someone was reading a text. Besides listening to a text, I would prefer to read the text."

Emotion & Expression:

The robotic nature of Professor AI was frequently mentioned. Students expressed that the AI lacked the empathy, emotion, and spontaneity a human professor would bring to the classroom. The stillness of the avatar, combined with monotone speech and a lack of facial expressions or gestures, made the AI seem detached and unnatural.

Many students felt disconnected because the AI lacked a human touch, which they believe is essential for keeping students engaged and motivated. The codes that appeared were "Robotic," "Unrealistic behavior," and "Lack of gestures."

Example quotes

> "I feel that it is AI and I don't like the feeling because AI is very robotic and stable and it is obvious that has no feeling."

> “The professor's lack of gestures and facial expressions and her constant stance mostly caused me to lose my attention.”
>
> “I assumed she was designed with a big smile to seem friendly, but sometimes it was too big, and it became a distraction. Some of her mimics also had a natural way which is clear that it has been worked upon, but not quite perfect.”

Interaction & Engagement:

A primary concern was the lack of interaction with Professor AI. Students were frustrated that they could not ask questions or engage with the content as they would have a chance to interact with a human professor. Many found the non-interactive nature of the course made it feel more like a passive learning experience, contributing to boredom and a lack of motivation. Real-time interaction (such as discussion and the ability to ask clarifying questions) was noted as something essential for an engaging learning environment according to the codes as such “Lack of interaction,” “Lack of engagement,” and “No communication for questions.”

Example quotes

> “It was not interactive at all. It should support me to join the class and engage with course materials.”
>
> “I don’t think interaction is sufficient. Face-to-face discussions are what make the knowledge solid.”
>
> “It is harder to communicate for lecture-related questions.”

Pace & Clarity:

Students frequently expressed concern about pace. Many found the Professor AI's speed too fast to follow, especially when the Professor AI did not allow breaks for reflection or interaction. The rapid pace led to difficulty grasping key concepts or processing the information delivered. Students expressed a need for the AI to slow down and offer pauses, allowing them to digest the information better. The codes appear as "fast pace," "fast speaking," and "no pause for thought."

Example quotes

> "The AI professor spoke very fast during the course so I had a hard time following it."
>
> "He/She didn't give us enough time to understand and digest what he/she was saying."
>
> "AI sometimes talks too fast - It can be more interactive - AI sometimes should take a deep breath."

Q3: What are the points that can be improved?

For this question, 125 students responded among 195, and based on the responses, seven themes were concluded. Table 9 shares the percentage split of the appearing codes within corresponding themes. Consequently, the most appealing themes are explained as follows:

Table 9. Themes for the Improvement Points of Professor AI

Theme	%
Humanization	36%
Content & Presentation Quality	30%
Engagement and Interactivity	23%
Pace and Speed	6%
Teaching	2%
Clarity	2%
Miscellaneous/Other	2%

Humanization:

Many responses focused on the need for the AI to appear more human-like, both in appearance and behavior. Students highlighted the importance of adding gestures, facial expressions, and emotional tone to the AI's presentation to make it feel more engaging and less robotic. Movement and facial expressions appear vital to creating a more immersive, lifelike experience. A more natural flow, akin to a human lecturer, would help improve the feeling of connection between the AI and students by the codes such as "Human-like," "Facial Expressions," and "Body Language."

Example quotes

"It should be more humane and it should be speaking like a real person."

"Facial expressions: Smiling while saying words with positive connotation such as "success" but frowns while saying "failure" which might not always be the correct way to deliver that lecture sentence."

"The use of body language can eliminate the problem of monotonous speech."

Content & Presentation Quality:

Several reviews about the quality of the content expressed that students felt that the content could be more concise. Including more real-life examples, visual aids, and relevant case studies would help contextualize the material and make it more engaging. Some students suggested that visual content (such as slides) could be better aligned with the spoken content for a more cohesive learning experience in accordance with the codes "Content," "Visuals," and "Real-life Examples."

Example quotes

"Long, long explanation, I don't prefer the kind of details. Normally, if we were in class, the lecturer realized the mood of the class. So the lecturer may respond according to the student's mood. The lecturer may make a joke, for example, if the class members feel bored."

"The presentation format can be changed into a 3D real-time background otherwise it seems like making a speech in front of a green screen."

"There should have been some kind of interface that offers different options or repeating or giving different examples while explaining something rather than just a video."

Engagement and Interactivity:

Many students emphasized the need for interactivity with the Professor AI, specifically the ability to ask questions or interact with the Professor AI during the lecture. Suggestions included incorporating an interactive Q&A feature, where students can ask questions and receive immediate answers, helping them clarify doubts in real-time. The lack of interaction made the lecture feel passive and more like watching a video rather than an active learning experience based on codes such as “interactivity,” “Q&A,” and “Engagement.”

Example quotes

> “If there is a way to make it an interactive thing, it will be amazing; asking and getting answers is good for students.”
>
> “Could have open-ended questions to keep the listener more engaged even if it’s not interactive.”
>
> “I think it should be more interactive. As a first step, students might ask their questions to AI whenever they want, and it answers the questions at the time questions are asked.”

CHAPTER 6

DISCUSSION

The objective of this study was to understand the factors affecting student acceptance of AI usage in higher education institutions for teaching purposes. UTAUT was the foundation of our theoretical model. We also included the mediating effect of attitude to develop behavioral intention in accordance with TAM, as one of the preliminary theories of UTAUT. Additionally, we extended the theoretical model by adding context-specific constructs. In this study, we investigated the effects of performance expectancy and trust on building a student attitude. We measured the impacts of student attitude, social influence, and facilitating conditions to building behavioral intention. Additionally, we investigated whether students are sensitive to learning from a human teacher.

Based on the PLS-SEM analysis, this study found a strong positive statistical relationship between performance expectancy and attitude similar to previous studies (Chatterjee & Bhattacharjee, 2020; Chen & Chang, 2011). This result demonstrates how a student's beliefs are positively impacted by their perception that utilizing AI-based educational solutions will improve their academic achievement and support H1.

This study supports that the social influence of peers, educators, or parents affects students' intention to develop behavior to use avatar teacher. Similar to the previous studies (Bilquise et al., 2023; Chen & Hwang, 2019; Shin, 2010), social influence is revealed as an important component in developing behavioral intention and supporting H2. This result indicates that students' intention to use AI-based educational solutions is influenced by social factors like parents, teachers, and peers. Views of social parties toward this new instructional technology should be considered when implementing such tools.

Unlike some of the previous studies (Chatterjee & Bhattacharjee, 2020; Chen & Chang, 2011), in this study, the relationship between facilitating conditions and behavioral intention is not statistically significant. However, there are other studies found that an insignificant relationship between FC and BI (AL-Nuaimi, Al Sawafi, Malik, & Al-Maroof, 2022). Insignificance can be driven by the lack of adequate technical and institutional support, which leads to the unnoticeable impact of facilitating conditions on intention (Alasmari & Zhang, 2019; AL-Nuaimi et al., 2022), and H3 was rejected. However, the implementation of avatar teacher for this did not necessitate any additional technical resources in the experimental setting in the university. Consequently, from the student's perspective, the facilitating conditions may not have significantly influenced their intention to engage with the avatar.

Results of PLS-SEM show that there is a statistically significant relationship between trust in avatar teacher and the development of positive attitudes. A positive relationship between TR and ATT is supported by others (Hamidi & Chavoshi, 2018; Lee & Choi, 2017), as to develop a positive attitude toward new technologies trust plays an important role and supports H4. Students' favorable attitudes about new technology are influenced by their faith in the technology and their trust that AI-based educational solutions can improve their academic achievement.

The positive influence of attitude to develop behavioral intention is supported in this study, similar to others (Chatterjee & Bhattacharjee, 2020; Cheung & Vogel, 2013), and H5 was accepted. This study indicates that there is a positive mediating relationship that states that a favorable attitude of students positively impacts their intention to use avatar teacher.

In this study, the moderating impact of preference for a human teacher on the relationship between ATT and BI was tested. However, the moderating effect of stickiness on a human teacher resulted in statistically insignificant. This contradicts the previous studies that indicate the negative moderating impact of ST (Chow, Herold, Choo, & Chan, 2012; Pillai et al., 2023) and H6 was rejected.

Based on the student sentiment explicitly analyzed the implementation of Professor AI in the experiment, students generally have a favorable opinion of Professor AI in the characteristics of speech and pronunciation quality, learning efficiency, and reliability of the content provided. Students perceive Professor AI as an effective tool for providing quick, clear, and concise lessons with clear and fluent delivery, along with well-organized content with ease of use and availability to make it a flexible and accessible teaching tool. However, according to the negative opinions and improvement areas highlighted in open-ended questions, teaching was viewed as negatively impacted by the speed and monotony of the avatar's content delivery. Additionally, students felt alienated from the material and the educational process because of the need for more interactive elements. Students felt disconnected because of the AI's incapacity to display human-like traits. Professor AI's unhuman-like characteristics, like the monotone tone of voice and speed, not pausing and providing no room to think and reflect students, and lack of interactivity and engagement create distractions and loss of interest and points to important improvement points. According to the PLS-SEM results, the moderating effect of stickiness on human teachers was not supported. However, the quantitative analysis revealed negative themes related to the non-human characteristics of Professor

AI. This suggests that while students may not insist on learning exclusively from human teachers, they do express a preference for more realistic avatars in virtual environments. This highlights the importance of designing avatars that better mimic human-like qualities, such as natural gestures, expressions, and interactions, to enhance the sense of realism and engagement. Addressing these preferences in future studies could lead to improved user experiences, increased acceptance of AI-driven teaching tools, and potentially greater learning outcomes in virtual and hybrid educational settings.

CHAPTER 7

CONCLUSION

This study aimed to capture the determinants of students' acceptance of AI-based educational solutions in the context of avatar usage with AI-based instructing materials. According to the results the analyzes, there is strong evidence for several hypothesized relationships. The influence of performance expectancy, trust, and social influence on attitude and behavioral intention displayed strong relationship. However, the lack of significance for facilitating conditions and moderating effect of stickiness on human teacher on the relationship between attitude and behavioral intention suggests that these constructs may require further investigation or a different theoretical framework to understand their role better. AI-based tools offer several benefits for teaching and learning, and by addressing these insights, higher education institutions can implement efficient strategies to promote the acceptance of artificial intelligence-based educational solutions among students and fully leverage the benefits of AI-based tools.

Students' positive perception of using AI-generated educational teaching tools to achieve better academic solutions positively affects their attitude toward accepting the new technology, according to the results of this study. Furthermore, the findings of this study highlight that trust in the new technology moderately fosters a positive attitude toward its acceptance, as the extent to which students believe that the new technology is credible and reliable.

Performance expectancy and trust have a positive influence on attitude. In contrast, the degree to which students favor or dislike the new technology in the empirical study and attitude also mediate the development of the behavioral intention to use the proposed AI-based tool. This relationship and the findings support the idea that students with a positive attitude toward the new technology are likelier to develop a positive intention to use it.

Additionally, students are influenced by social factors, such as the opinions of peers, family, or societal norms, to develop an attitude toward and positive intention toward using new technology. This finding highlights the importance of considering social and cultural contexts when implementing AI-based teaching tools in higher education institutions.

Facilitating conditions, such as availability of resources or technical support, do not directly drive behavioral intention in the context of this study. This may indicate that other factors, such as attitude or social influence, play a more dominant role. Additionally, the development of Professor AI and its use in the teaching environment did not require any additional technical resources or support for this study's experimental setting applied in the higher education environment; thus, facilitating conditions might lead to an insignificant relationship from the student perspective. This result can be supported by the sentiment collected and analyzed in the thematic analysis indicated in the user experience theme. Professor AI provides ease of use and access in the learning environment.

Similarly, a moderating factor of stickiness to human teachers appeared insignificant, and the study supported its influence on attitude on behavioral intention as unmeaningful. According to the findings through thematic analysis, negative student sentiment shared on Professor AI's mechanical and inhumane appearance and expressions were expressed as an improvement area. This creates a contradiction between the moderating impact of stickiness to human teachers on behavioral intention. It might indicate that students may not strictly prefer to be taught by human teachers rather than using avatar instructors. However, the preference for more human-like AI instructors specifically indicated for Professor AI can require a future investigation with refinements.

Based on the student sentiment explicitly analyzed the implementation of Professor AI in the experiment, students generally have a favorable opinion of Professor AI in the characteristics of speech and pronunciation quality, learning efficiency, and reliability of the content provided. Students perceive Professor AI as an effective tool for providing quick, clear, and concise lessons with clear and fluent delivery, along with well-organized content with ease of use and availability to make it a flexible and accessible teaching tool. However, according to the negative opinions and improvement areas highlighted in open-ended questions, teaching was viewed as negatively impacted by the speed and monotony of the avatar's content delivery. Additionally, students felt alienated from the material and the educational process because of the need for more interactive elements. Students felt disconnected because of the AI's incapacity to display human-like traits. Professor AI's unhuman-like traits, like the monotone tone of voice and speed, not pausing and providing no room to think and reflect students, and lack of interactivity and engagement create distractions and loss of interest and points to important improvement points.

In conclusion, this study aimed to capture the determinants of students' acceptance of AI-based educational solutions in the context of avatar usage with AI-based instructing materials. Our findings emphasize the critical role of performance expectancy of the students to use new technology and trust towards it, which shapes the student attitude. The social influence of peers or families is another factor that impacts the development of behavioral intention to use the new technology, together with a positive attitude. Additionally, our study reveals a need for innovation to address emotional engagement and interactivity limitations while designing and implementing technologies like Professor AI. The insights we derived from our research guide educators, developers, and policymakers seeking to implement AI solutions into higher education. Lastly, as we combine quantitative analyses with qualitative insights, our study contributes to the literature on AI acceptance in education to understand student perception deeper, and shares highlights for AI-driven learning experiences.

CHAPTER 8

LIMITATIONS AND FUTURE RESEARCH

While this study has its limitations, it also opens exciting avenues for future research. Our one-time study, which gathered student perceptions and tested hypotheses in a single in-class experimental setting, can serve as a springboard for more extensive, longitudinal research. This could provide a deeper understanding of student acceptance and reflections on Professor AI over time.

Our experiment was conducted with students from a technical department, who possess a strong technical background. To broaden the scope, the study could be extended to various departments such as social sciences in higher education institutions, fostering an interdisciplinary testing environment. Furthermore, while our study was conducted in one institution, future research could incorporate multiple institutions to expand the sample size and evaluate the influence of demographics, such as geographical factors.

In our first theoretical model, we included Effort Expectancy (EE) based on UTAUT, hypothesizing that it positively impacts student attitude towards developing a usage intention for the new technology. However, this relationship appeared not significant in the model analysis. One of the indicators of EE was creating cross-loading between constructs. We dropped related indicator of EE from the model in the second run, however by doing so BI was displaying high VIF values which leads to multicollinearity. As it leads to errors in the theoretical model, we dropped EE construct in the final model. With a larger sample size, we can revisit this and potentially include

EE in the theoretical model in future studies, underscoring the importance of a robust sample size in research.

For our data collection, we implemented a questionnaire instrument. Through the open-ended questions, we aimed to capture student sentiment that is not reflected in the theoretical model, particularly their apprehension towards developing AI-based content and AI instructors. In future studies, we see the potential for interviews to be conducted, providing deeper insights into student perception and offering opportunities for the improvement of AI instruments.

Additionally, in this study, avatar appearance in the experiment was constant. In future studies, avatar characteristics such as physical appearance, gender, and race can be varied to understand these factors as the determinants of student acceptance factors.

APPENDIX A

ETHICS COMMITTEE APPROVAL

T.C.
BOĞAZİÇİ ÜNİVERSİTESİ REKTÖRLÜĞÜ
Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (Sbinarek)

Sayı : E-84391427-050.01.04-174952 03.04.2024
Konu : 2024-10T Kayıt Numaralı Başvurunuz Hakkında

Sayın Dr. Öğr. Üyesi Aysun BOZANTA HAKYEMEZ

Tez danışmanlığını yürüttüğünüz öğrenciniz Fatma Kasapoğlu'nun "New age of teaching with Professor AI" başlıklı projesi ile Boğaziçi Üniversitesi Sosyal ve Beşeri Bilimler İnsan Araştırmaları Etik Kurulu (SBİNAREK)'e yaptığınız 2024-10T kayıt numaralı başvuru 14.03.2024 tarih ve 2024/02 sayılı kurul toplantısında incelenmiş ve projeye etik onay verilmesi uygun bulunmuştur.

Bu karar tüm üyelerin toplantıya on-line olarak katılımıyla ve oybirliği ile alınmıştır. Onay mektubu tüm üyeler adına Komisyon Başkanı tarafından e-imzalanmıştır. Bilgilerinizi rica ederiz.

Saygılarımızla,

Dr. Öğr. Üyesi Işıl ERDUYAN
Kurul Başkanı

Bu belge, güvenli elektronik imza ile imzalanmıştır.

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APPENDIX B

PROMPTING EXAMPLES

I want to generate a course content for university students in presentation format. the course is about "data representation". I will give you a topic for each slide of presentation and I want you to generate me a slide content about that topic, following to the slide content share me a narrative that explains that slide. I want the slide contents comprehensive, highlighting important aspects. I want the slide narratives in detailed explanation with good examples to make audience understand

Memory updated

Great! Please provide the topics for each slide, and I'll generate both the content and narratives for you.

here's the objectives of this course. give me an introduction to the course: Describe numbering systems and their use in data representation
Compare different data representation methods
Summarize the CPU data types and explain how nonnumeric data is represented
Describe common data structures and their uses

Here's an introduction to the course based on the objectives you provided:

Slide Title: Introduction to Data Representation

Slide Content:

- **Numbering Systems:** Understanding binary, decimal, hexadecimal, and their application in computing.
- **Data Representation Methods:** Binary coding, ASCII, Unicode, floating-point representation.
- **CPU Data Types & Non-Numeric Data Representation:** How data types like integers, floating points, and characters are stored and processed.
- **Common Data Structures:** Arrays, linked lists, stacks, and their roles in organizing and managing data.

next slide for "E-commerce Today".

Slide Content: E-Commerce Today

- Rapid growth in online shopping and digital transactions.
- Increased use of mobile devices for shopping (m-commerce).
- The importance of social media in influencing purchasing decisions.
- Enhanced payment options (e-wallets, cryptocurrencies).
- Focus on customer experience and personalization.
- Growing concerns around data privacy and security.

Narrative:

Let's take a moment to explore **e-commerce today**. It's a dynamic landscape that's constantly evolving, and there are several key elements driving its growth and shaping how we shop.

First, we're witnessing **rapid growth** in online shopping. Thanks to advancements in technology and changing consumer behaviors, more people are turning to e-commerce for their purchases. Whether it's clothing, groceries, or electronics, the internet has become a primary shopping destination for many.

An exciting development is the increasing use of **mobile devices** for shopping, often referred to as **m-commerce**. Smartphones have become an essential tool for browsing and buying products on the go. With just a few taps, you can order your favorite coffee or book a last-minute hotel room. This convenience is driving e-commerce forward, making it accessible anywhere and anytime.

Another crucial factor is the role of **social media** in influencing purchasing decisions. Platforms like Instagram, TikTok, and Facebook have transformed into powerful marketing tools, with brands using targeted ads and influencer partnerships to reach potential customers. Social media isn't just about connecting with friends anymore; it's a place where people discover and buy products.

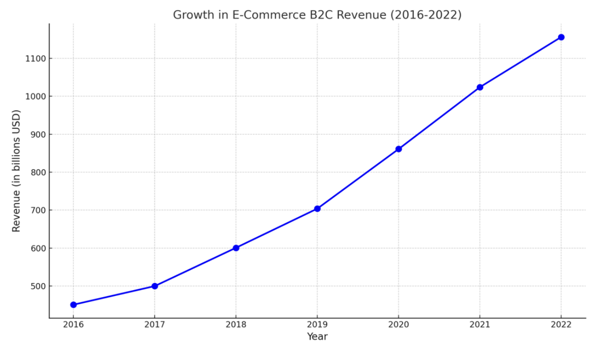
Speaking of buying, we're seeing **enhanced payment options** making transactions easier. From e-wallets like **PayPal** and **Venmo** to the emergence of cryptocurrencies like **Bitcoin**, consumers now have more choices than ever. These options not only streamline the checkout process but also cater to a broader range of preferences.

As competition heats up in e-commerce, companies are putting more emphasis on **customer experience and personalization**. Brands are leveraging data analytics to offer tailored recommendations, special promotions, and personalized communication, making shopping feel more individual and engaging. This is where a well-designed digital interface can make a huge difference, enhancing customer satisfaction.

However, with all these advancements come growing concerns about **data privacy and security**. As businesses collect more data to improve their services, consumers are becoming increasingly cautious about how their information is used. Stronger regulations, like the GDPR in Europe, are being implemented to protect consumers and build trust in the digital marketplace.

In summary, e-commerce today is characterized by innovation, convenience, and personalization—but it's also a space where businesses must navigate the challenges of data security and consumer trust. It's an exciting time to be involved in e-commerce, and understanding these trends is crucial for anyone looking to thrive in this rapidly changing environment.

the next slide for "the growth of e-commerce". give me a graph for "growth in e-commerce B2C revenue"



Here's the graph showing the **growth in e-commerce B2C revenue** from 2016 to 2022. You can see a clear upward trend, illustrating how the revenue has increased significantly over the years.

Slide Content: The Growth of E-Commerce

- B2C e-commerce revenue has skyrocketed in recent years.

make the introduction a little bit technical. prior to this course, students learnt data flow diagrams then we will continue with data dictionary.

Memory updated

Here's a more technical introduction that builds on the students' prior knowledge of data flow diagrams (DFDs) and sets up the continuation with data dictionaries:

Slide 1: Introduction to Data and Process Modeling

Narrative:

Welcome back, everyone! Now that you've tackled data flow diagrams (DFDs), you already have a solid foundation for understanding how information moves through a system. Think of it like a map showing how ingredients pass through each station in a kitchen—flour goes here, eggs go there, and somehow it all comes together into a dish.

But as you may have realized, knowing where the data flows is only part of the picture. We also need to answer some important questions: *What* exactly is that data? How is it defined? How do we make sure everyone working in our "kitchen" knows what "flour" or "eggs" means in this process? That's where *data dictionaries* come into play.

In today's session, we'll build on what you already know about DFDs and explore *data and process modeling* more comprehensively. 'll learn how these models provide a structured way to represent data elements, relationships, and the flow of processes within an

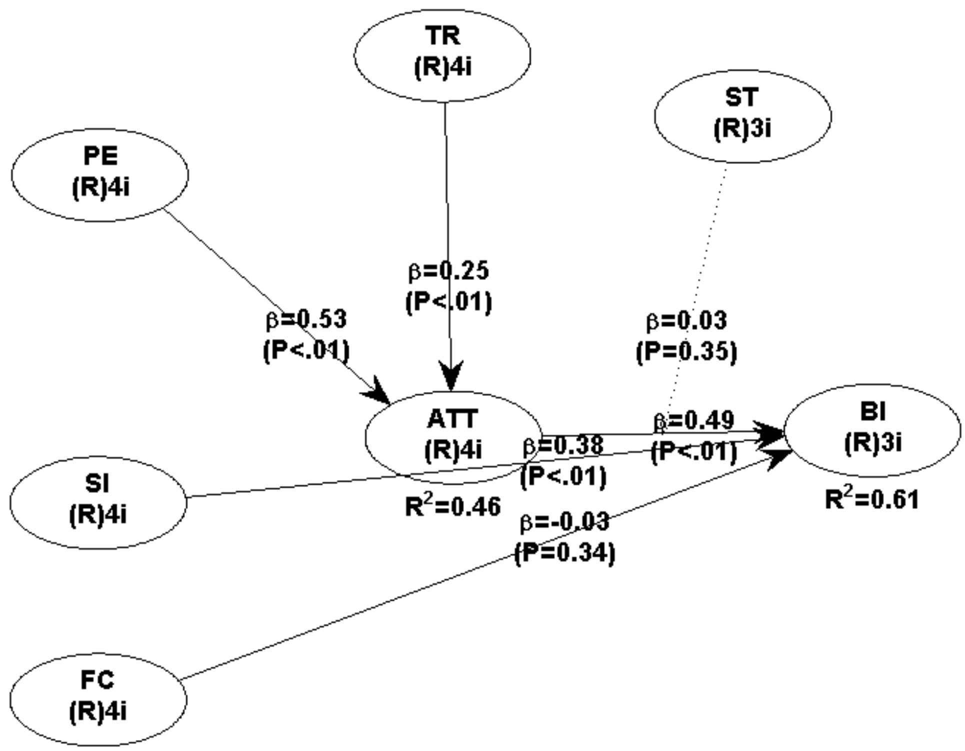
APPENDIX C

QUESTIONNAIRE

Main construct	Indicators/items	References
Performance Expectacy (PE)	I would find the Professor AI useful in my university education	(Venkatesh et al., 2003)
	Using Professor AI enables me to learn course subjects quicker.	
	Using Professor AI increases my productivity.	
	Using Professor AI improves the outcomes of my learnings.	
Effort Expectancy (EE)	Interaction with the Professor AI would be clear and understandable.	(Venkatesh et al., 2003)
	By using the Professor AI, I am able to obtain learning services easily.	
	The use of Professor AI is easy.	
Social Influence (SI)	Friends whose opinions I value would prefer me to use Professor AI.	(Venkatesh et al., 2003)
	People who influence my behavior would think that I should use the Professor AI.	
	The instructors in my institution would have been helpful to use Professor AI.	
	In general, my institution has positive views on adopting AI and related technologies to enhance learning processes.	
Facilitating Conditions (FC)	My institute has the necessary resources to use Professor AI.	(Chatterjee & Bhattacharjee, 2020)
	My institute would sponsor AI generated learning opportunity.	
	The classrooms of my institute are equipped with necessary devises for using Professor AI for teaching purpose.	
	My institute encourages its staff to use AI technology.	
Trust (TR)	I think I would have faith in the information provided by the Professor AI.	(Lee & Choi, 2017)
	I think that the Professor AI would provide unbiased and accurate information and recommendations.	
	I think that Professor AI would be honest and trustworthy.	
	I think that Professor AI would provide a reliable service.	
Attitude (ATT)	I like using AI-based systems like Professor AI for my study.	(Li, 2023)
	I feel good about using AI-based systems like Professor AI for learning purposes.	
	Using AI-based systems like Professor AI is an attractive way for me to study.	
	Overall, my attitude towards AI-based systems like Professor AI is positive.	
Stickiness to Human Teacher (ST)	I want to learn and study from the professor in class than Professor AI.	(Pillai et al., 2023)
	I would always ask my study-related queries to my professor during the lecture.	
	I always prefer my professor in class to AI solutions like Professor AI.	
Behavioral Intention (BI)	I intend to use the Professor AI in the future.	(Venkatesh et al., 2012)
	I would always try to use the Professor AI for my learning needs.	
	I plan to use the Professor AI frequently.	

APPENDIX D

PLS-SEM OUTPUT OF STRUCTURAL MODEL



REFERENCES

Adamo-Villani, N., & Dib, H. N. (2016). A study of the effects of teaching avatars on students' learning of surveying mathematics. *International Journal of Information and Communication Technology Education*, *12*(2), 1–13. https://doi.org/10.4018/IJICTE.2016040101

Ahire, S. L., & Devaraj, S. (2001). An empirical comparison of statistical construct validation approaches. *IEEE Transactions on Engineering Management*, *48*(3), 319–329. https://doi.org/10.1109/17.946530

AL-Nuaimi, M. N., Al Sawafi, O. S., Malik, S. I., & Al-Maroof, R. S. (2022). Extending the unified theory of acceptance and use of technology to investigate determinants of acceptance and adoption of learning management systems in the post-pandemic era: A structural equation modeling approach. *Interactive Learning Environments*, 1–27. https://doi.org/10.1080/10494820.2022.2127777

Alasmari, T., & Zhang, K. (2019). Mobile learning technology acceptance in Saudi Arabian higher education: An extended framework and A mixed-method study. *Education and Information Technologies*, *24*(3), 2127–2144. https://doi.org/10.1007/s10639-019-09865-8

Algerafi, M. A. M., Zhou, Y., Alfadda, H., & Wijaya, T. T. (2023). Understanding the factors influencing higher education students' intention to adopt artificial intelligence-based robots. *IEEE Access*, *11*, 99752–99764. https://doi.org/10.1109/ACCESS.2023.3314499

Baker, T., & Smith, L. (2019). Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges. Retrieved from https://media.nesta.org.uk/documents/Future_of_AI_and_education_v5_WEB.pdf

Bañeres, D., Rodríguez-González, M. E., Guerrero-Roldán, A.-E., & Cortadas, P. (2023). An early warning system to identify and intervene online dropout learners. *International Journal of Educational Technology in Higher Education*, *20*(1), 3. https://doi.org/10.1186/s41239-022-00371-5

Bilquise, G., Ibrahim, S., & Salhieh, S. M. (2023). Investigating student acceptance of an academic advising chatbot in higher education institutions. *Education and Information Technologies*, *29*(5), 6357–6382. https://doi.org/10.1007/s10639-023-12076-x

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). Artificial intelligence trends in education: A narrative overview. *Procedia Computer Science*, *136*, 16–24. https://doi.org/10.1016/j.procs.2018.08.233

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5), 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Chaudhry, I. S., Sarwary, S. A. M., El Refae, G. A., & Chabchoub, H. (2023). Time to revisit existing student's performance evaluation approach in higher education sector in a new era of ChatGPT — A Case Study. *Cogent Education*, *10*(1), 2210461. https://doi.org/10.1080/2331186X.2023.2210461

Chen, K. Y., & Chang, M. L. (2011). User acceptance of 'near field communication' mobile phone service: an investigation based on the 'unified theory of acceptance and use of technology' model. *The Service Industries Journal*, *33*(6), 609–623. https://doi.org/10.1080/02642069.2011.622369

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, *8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Chen, P.-Y., & Hwang, G.-J. (2019). An empirical examination of the effect of self-regulation and the unified theory of acceptance and use of technology (UTAUT) factors on the online learning behavioural intention of college students. *Asia Pacific Journal of Education*, *39*(1), 79–95. https://doi.org/10.1080/02188791.2019.1575184

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education*, *63*, 160–175. https://doi.org/10.1016/j.compedu.2012.12.003

Chiyangwa, T. B., & (Trish) Alexander, P. M. (2016). Rapidly co-evolving technology adoption and diffusion models. *Telematics and Informatics*, *33*(1), 56–76. https://doi.org/10.1016/j.tele.2015.05.004

Chow, M., Herold, D.K., Choo, T.M., & Chan, K. (2012). Extending the technology acceptance model to explore the intention to use Second Life enhancing healthcare education, *Computers and Education, 59*, 1136-1144.

Cox, J. (2012). Information systems user security: A structured model of the knowing-doing gap. *Computers in Human Behavior*, *28*(5), 1849–1858. https://doi.org/10.1016/j.chb.2012.05.003

Crawford, J., Cowling, M., & Allen, K.-A. (2023). Leadership is needed for ethical ChatGPT: Character, assessment, and learning using artificial intelligence (AI). *Journal of University Teaching and Learning Practice*, *20*(3). https://doi.org/10.53761/1.20.3.02

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education*, *20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Daniels, D., & Lee, J. S. (2022). The impact of avatar teachers on student learning and engagement in a virtual learning environment for online STEM courses. In P. Zaphiris & A. Ioannou (Eds.), *Learning and Collaboration Technologies: Novel Technological Environments, LCT 2022, PT II* (Vol. 13329, pp. 158–175)., doi:10.1007/978-3-031-05675-8_13

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

De Martino, J. M., Silva, I. R., Bolognini, C. Z., Costa, P. D. P., Kumada, K. M. O., Coradine, L. C., Brito, P. H. D. S., Do Amaral, W. M., Benetti, Â. B., Poeta, E. T., Angare, L. M. G., Ferreira, C. M., & De Conti, D. F. (2017). Signing avatars: Making education more inclusive. *Universal Access in the Information Society*, *16*(3), 793–808. https://doi.org/10.1007/s10209-016-0504-x

Deo, R. C., Yaseen, Z. M., Al-Ansari, N., Nguyen-Huy, T., Langlands, T. A. M., & Galligan, L. (2020). Modern artificial intelligence model development for undergraduate student performance prediction: An investigation on engineering mathematics courses. *IEEE Access*, 8, 136697–136724. https://doi.org/10.1109/ACCESS.2020.3010938

Dishaw, M.T., & Strong, D.M. (1999). Extending the technology acceptance model with task-technology fit constructs. *Inf. Manag., 36*, 9-21.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71.

Dunsworth, Q., & Atkinson, R. K. (2007). Fostering multimedia learning of science: Exploring the role of an animated agent's image. *Computers & Education*, *49*(3), 677–690. https://doi.org/10.1016/j.compedu.2005.11.010

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

F. Hair Jr, J., Sarstedt, M., Hopkins, L., & G. Kuppelwieser, V. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Fernandes, T., & Oliveira, E. (2021). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, *122*, 180–191. https://doi.org/10.1016/j.jbusres.2020.08.058

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Reading, MA: Addison-Wesley.

George, B., & Wooden, O. (2023). Managing the strategic transformation of higher education through artificial intelligence. *Administrative Sciences*, *13*(9), 196. https://doi.org/10.3390/admsci13090196

Grivokostopoulou, F., Perikos, I., & Hatzilygeroudis, I. (2017). An educational system for learning search algorithms and automatically assessing student performance. *International Journal of Artificial Intelligence in Education*, *27*(1), 207–240. https://doi.org/10.1007/s40593-016-0116-x

Haenlein, M., & Kaplan, A. M. (2004). A beginner's guide to partial least squares analysis. *Understanding Statistics*, *3*(4), 283–297. https://doi.org/10.1207/s15328031us0304_4

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

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hamidi, H., & Chavoshi, A. (2018). Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the University of Technology. *Telematics and Informatics*, *35*(4), 1053–1070. https://doi.org/10.1016/j.tele.2017.09.016

Hannan, E., & Liu, S. (2021). AI: New source of competitiveness in higher education. *Competitiveness Review: An International Business Journal*, *33*(2), 265–279. https://doi.org/10.1108/CR-03-2021-0045

Hirata, Y. (2023). Do avatar-assisted virtual classrooms work for students with low speaking confidence?: A qualitative study. *Interactive Technology and Smart Education*, *20*(3), 335–349. https://doi.org/10.1108/ITSE-10-2022-0142

Howard, R., Restrepo, L., & Chang, C.-Y. (2017). Addressing individual perceptions: An application of the unified theory of acceptance and use of technology to building information modelling. *International Journal of Project Management*, *35*(2), 107–120. https://doi.org/10.1016/j.ijproman.2016.10.012

Jia, F., Sun, D., & Looi, C. (2024). Artificial intelligence in science education (2013–2023): Research trends in ten years. *Journal of Science Education and Technology*, *33*(1), 94–117. https://doi.org/10.1007/s10956-023-10077-6

Johnson, W. L., & Lester, J. C. (2016). Face-to-face interaction with pedagogical agents, twenty years later. *International Journal of Artificial Intelligence in Education*, *26*(1), 25–36. https://doi.org/10.1007/s40593-015-0065-9

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kerly, A., Hall, P., & Bull, S. (2007). Bringing chatbots into education: Towards natural language negotiation of open learner models. *Knowledge-Based Systems*, *20*(2), 177–185. https://doi.org/10.1016/j.knosys.2006.11.014

Kock, N., & Lynn, G. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. Journal of the Association of Information Systems, 13(7), 546–580. https://doi.org/10.17705/1jais.00302

Kock, N. (2015a). Common nethod bias in PLS-SEM: A full collinearity assessment approach. *International Journal of E-Collaboration, 11(4), 1–10.* https://doi.org/10.4018/ijec.2015100101

Kock, N. (2015b). One-tailed or two-tailed p values in PLS-SEM?: *International Journal of E-Collaboration*, *11*(2), 1–7. https://doi.org/10.4018/ijec.2015040101

Kock, N. (2015c). *WarpPLS 5.0 User Manua*l. Laredo, TX:ScriptWarp Systems.

Kock, N. (2018). Should bootstrapping be used in PLS-SEM? Toward stable p-value calculation methods. *Journal of Applied Structural Equation Modeling*, *2*(1), 1–12. https://doi.org/10.47263/JASEM.2(1)02

Kuhail, M. A., Alturki, N., Alramlawi, S., & Alhejori, K. (2023). Interacting with educational chatbots: A systematic review. *Education and Information Technologies*, *28*(1), 973–1018. https://doi.org/10.1007/s10639-022-11177-3

Kumar, A., Saudagar, A. K. J., Alkhathami, M., Alsamani, B., Khan, M. B., Hasanat, M. H. A., Ahmed, Z. H., Kumar, A., & Srinivasan, B. (2023). Gamified learning and assessment using ARCS with next-generation AIoMT integrated 3D animation and virtual reality simulation. *Electronics*, *12*(4), 835. https://doi.org/10.3390/electronics12040835

Lahav, O., Talis, V., Cinamon, R. G., & Rizzo, A. (2020). Virtual interactive consulting agent to support freshman students in transition to higher education. *Journal of Computing in Higher Education*, *32*(2), 330–364. https://doi.org/10.1007/s12528-019-09237-8

Lancelot Miltgen, C., Popovič, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the "Big 3" of technology acceptance with privacy context. *Decision Support Systems*, *56*, 103–114. https://doi.org/10.1016/j.dss.2013.05.010

Lee, S., & Choi, J. (2017). Enhancing user experience with conversational agent for movie recommendation: Effects of self-disclosure and reciprocity. *International Journal of Human-Computer Studies*, *103*, 95–105. https://doi.org/10.1016/j.ijhcs.2017.02.005

Li, K. C., & Wong, B. T.-M. (2021). Features and trends of personalised learning: A review of journal publications from 2001 to 2018. *Interactive Learning Environments*, *29*(2), 182–195. https://doi.org/10.1080/10494820.2020.1811735

Liu, S., & Hao, F. (2024). Engaging with avatar in virtual regenerative tourism. *Journal of Travel & Tourism Marketing*, *41*(6), 864–879. https://doi.org/10.1080/10548408.2024.2350053

Lochmiller, C. (2021). Conducting thematic analysis with qualitative data. *The Qualitative Report*. https://doi.org/10.46743/2160-3715/2021.5008

McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (2006). A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12. https://doi.org/10.1609/aimag.v27i4.1904

Marchewka, J. T., & Kostiwa, K. (2007). An application of the UTAUT model for understanding student perceptions using course management foftware. *Communications of the IIMA*, *7*(2). https://doi.org/10.58729/1941-6687.1038

Moon, J.-W., & Kim, Y.-G. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*, *38*(4), 217–230. https://doi.org/10.1016/S0378-7206(00)00061-6

Muthmainnah, Ibna Seraj, P. M., & Oteir, I. (2022). Playing with AI to investigate human-computer interaction technology and improving critical thinking skills to pursue 21st century age. *Education Research International*, *2022*, 1–17. https://doi.org/10.1155/2022/6468995

Olushola, T., & Abiola, J. O. (2017). The efficacy of technology acceptance model: A review of applicable theoretical models in information technology researches. *Journal of Research in Business and Management, 4*(11), 70–83. Retrieved from https://www.questjournals.org/jrbm/papers/vol4-issue11/J4117083.pdf

Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies*, *27*(6), 7893–7925. https://doi.org/10.1007/s10639-022-10925-9

Pallant, J. (2013). *SPSS survival manual: A step by step guide to data analysis using IBM SPSS* (5th ed.). McGraw-Hill Education (UK).

Pérez, J. Q., Daradoumis, T., & Puig, J. M. M. (2020). Rediscovering the use of chatbots in education: A systematic literature review. *Computer Applications in Engineering Education*, *28*(6), 1549–1565. https://doi.org/10.1002/cae.22326

Picciano, A. (2019). Artificial Intelligence and the Academy's Loss of Purpose. *Online Learning*, *23*(3). https://doi.org/10.24059/olj.v23i3.2023

Pillai, R., Sivathanu, B., Metri, B., & Kaushik, N. (2023). Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education. *Information Technology & People*, *37*(1), 328–355. https://doi.org/10.1108/ITP-02-2021-0152

Pinto Dos Santos, D., Giese, D., Brodehl, S., Chon, S. H., Staab, W., Kleinert, R., Maintz, D., & Baeßler, B. (2019). Medical students' attitude towards artificial intelligence: A multicentre survey. *European Radiology*, *29*(4), 1640–1646. https://doi.org/10.1007/s00330-018-5601-1

Popenici, S. A. D., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, *12*(1), 22. https://doi.org/10.1186/s41039-017-0062-8

Qi, S., Liu, L., Kumar, B. S., & Prathik, A. (2022). An English teaching quality evaluation model based on Gaussian process machine learning. *Expert Systems*, *39*(6), e12861. https://doi.org/10.1111/exsy.12861

Raffaghelli, J. E., Rodríguez, M. E., Guerrero-Roldán, A.-E., & Bañeres, D. (2022). Applying the UTAUT model to explain the students' acceptance of an early warning system in Higher Education. *Computers & Education*, *182*, 104468. https://doi.org/10.1016/j.compedu.2022.104468

Rawas, S. (2024). ChatGPT: Empowering lifelong learning in the digital age of higher education. *Education and Information Technologies*, *29*(6), 6895–6908. https://doi.org/10.1007/s10639-023-12114-8

Roy, R., Babakerkhell, M. D., Mukherjee, S., Pal, D., & Funilkul, S. (2022). Evaluating the intention for the adoption of artificial intelligence-based robots in the university to educate the students. *IEEE Access*, *10*, 125666–125678. https://doi.org/10.1109/ACCESS.2022.3225555

Saldana, J. (2013). *The coding manual for qualitative researchers* (2nd ed.). Sage.

Sánchez-Prieto, J. C., Cruz-Benito, J., Therón, R., & García-Peñalvo, F. (2020). Assessed by machines: development of a TAM-based tool to measure AI-based assessment acceptance among students. *International Journal of Interactive Multimedia and Artificial Intelligence*, *6*(4), 80. https://doi.org/10.9781/ijimai.2020.11.009

Schroeder, K. T., Hubertz, M., Van Campenhout, R., & Johnson, B. G. (2022). Teaching and learning with AI-generated courseware: Lessons from the classroom. *Online Learning*, *26*(3). https://doi.org/10.24059/olj.v26i3.3370

Schroeder, N. L., Adesope, O. O., & Gilbert, R. B. (2013). How effective are pedagogical agents for learning? A meta-analytic review. *Journal of Educational Computing Research*, *49*(1), 1–39. https://doi.org/10.2190/EC.49.1.a

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. *Journal of Consumer Research, 15*(3), 325. https://doi.org/10.1086/209170

Shiao, Y.-T., Chen, C.-H., Wu, K.-F., Chen, B.-L., Chou, Y.-H., & Wu, T.-N. (2023). Reducing dropout rate through a deep learning model for sustainable education: Long-term tracking of learning outcomes of an undergraduate cohort from 2018 to 2021. *Smart Learning Environments*, *10*(1), 55. https://doi.org/10.1186/s40561-023-00274-6

Shin, D.-H. (2010). MVNO services: Policy implications for promoting MVNO diffusion. *Telecommunications Policy*, *34*(10), 616–632. https://doi.org/10.1016/j.telpol.2010.07.001

Smutny, P., & Schreiberova, P. (2020). Chatbots for learning: A review of educational chatbots for the Facebook Messenger. *Computers & Education*, *151*, 103862. https://doi.org/10.1016/j.compedu.2020.103862

Stonkiene, M., Matkeviciene, R., & Vaiginiene, E. (2016). Evaluation of the national higher education system's competitiveness: Theoretical model. *Competitiveness Review*, *26*(2), 116–131. https://doi.org/10.1108/CR-06-2015-0055

Taskiran, A., & Goksel, N. (2022). Automated feedback and teacher feedback: Writing achievement in learning English as a foreign language at a distance. *Turkish Online Journal of Distance Education, 23*(2), 120–139. https://doi.org/10.17718/tojde.1096260

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

Thanyadit, S., Heintz, M., & Law, E. L.-C. (2023). Tutor in-sight: Guiding and visualizing students' attention with mixed reality avatar presentation tools. *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*, 1–20. https://doi.org/10.1145/3544548.3581069

Timms, M. J. (2016). Letting artificial intelligence in education out of the box: educational cobots and smart classrooms. *International Journal of Artificial Intelligence in Education*, *26*(2), 701–712. https://doi.org/10.1007/s40593-016-0095-y

Venkatesh, Morris, Davis, & Davis. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

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

Vermeir, I., & Verbeke, W. (2006). Sustainable food consumption: Exploring the consumer "attitude – behavioral intention" gap. *Journal of Agricultural and Environmental Ethics*, *19*(2), 169–194. https://doi.org/10.1007/s10806-005-5485-3

Vittorini, P., Menini, S., & Tonelli, S. (2021). An AI-based system for formative and summative assessment in data science courses. *International Journal of Artificial Intelligence in Education*, *31*(2), 159–185. https://doi.org/10.1007/s40593-020-00230-2

Wu, L.-H., Wu, L.-C., & Chang, S.-C. (2016). Exploring consumers' intention to accept smartwatch. *Computers in Human Behavior*, *64*, 383–392. https://doi.org/10.1016/j.chb.2016.07.005

Xiao, M., & Yi, H. (2021). Building an efficient artificial intelligence model for personalized training in colleges and universities. *Computer Applications in Engineering Education*, *29*(2), 350–358. https://doi.org/10.1002/cae.22235

Yu, H., Miao, C., Leung, C., & White, T. J. (2017). Towards AI-powered personalization in MOOC learning. *Npj Science of Learning*, *2*(1), 15. https://doi.org/10.1038/s41539-017-0016-3

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0

Zhang, C., Hofmann, F., Plößl, L., & Gläser-Zikuda, M. (2024). Classification of reflective writing: A comparative analysis with shallow machine learning and pre-trained language models. *Education and Information Technologies*, *29*(16), 21593–21619. https://doi.org/10.1007/s10639-024-12720-0

Zheng, L., Fan, Y., Chen, B., Huang, Z., LeiGao, & Long, M. (2023). An AI-enabled feedback-feedforward approach to promoting online collaborative learning. *Education and Information Technologies*, *29*(9), 11385–11406. https://doi.org/10.1007/s10639-023-12292-5

Zhou, C. (2023). Integration of modern technologies in higher education on the example of artificial intelligence use. *Education and Information Technologies*, *28*(4), 3893–3910. https://doi.org/10.1007/s10639-022-11309-9

Zhu, L., Liu, G., Lv, S., Chen, D., Chen, Z., & Li, X. (2023). An intelligent boosting and decision-tree-regression-based score prediction (BDTR-SP) method in the reform of tertiary education teaching. *Information*, *14*(6), 317. https://doi.org/10.3390/info14060317