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# Key Factors Influencing Design Learners' Behavioral Intention in Human-AI Collaboration Within the Educational Metaverse

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**Abstract:** This study investigates the key factors which influence design learners' behavioral intention to collaborate with AI in the educational metaverse (EMH-AIc). Engaging design learners in EMH-AIc enhances learning efficiency, personalizes learning experiences, and supports equitable and sustainable design education. However, limited research has focused on these influencing factors, leading to a lack of theoretical grounding for user behavior in this context. Drawing on social cognitive theory (SCT), this study constructs a three-dimensional theoretical model comprising the external environment, individual cognition, and behavior, validated within an EMH-AIc setting. By using Spatial.io's Apache Art Studio as the experimental platform and analyzing data from 533 design learners with SPSS 27.0, SmartPLS 4.0, and partial least squares structural equation modeling (PLS-SEM), this study identifies those rewards, teacher support, and facilitating conditions in the external environment, with self-efficacy, outcome expectation, and trust in cognition also significantly influencing behavioral intention. Additionally, individual cognition mediates the relationship between the external environment and behavioral intention. This study not only extends SCT application within the educational metaverse but also provides actionable insights for optimizing design learning experiences, contributing to the sustainable development of design education.

**Keywords:** educational metaverse; sustainable design education; human-AI collaboration; social cognitive theory; behavioral intention

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## 1. Introduction

Educational equity is a core issue of global sustainable development [1]. The United Nations Sustainable Development Goals (SDGs) point out that ensuring inclusive and equitable quality education and promoting lifelong learning for all are the core tasks of global education [2]. In design education, geographical barriers, uneven resources, and lack of opportunities for interdisciplinary collaboration pose serious challenges to educational equity. This imbalance restricts the sustainable development of design education, especially for students with limited resources who find it difficult to obtain the same learning opportunities and support as other students [3,4]. With the widespread application of emerging technologies such as virtual reality (VR), augmented reality (AR), and artificial intelligence (AI) in the design industry, the problem of uneven distribution of traditional educational resources has become more prominent, placing higher demands on the rapid transformation of design education. Therefore, this study aims to explore how to effectively alleviate educational inequality by applying artificial intelligence and the educational metaverse, thus promoting the sustainable development of design education.

The rise of the educational metaverse provides a new opportunity to solve the unfair problems encountered in design education. The educational metaverse breaks through the geographical and resource limitations of traditional education through immersive and personalized learning experiences [5–7]. For example, Google Expeditions allows students to virtually tour museums and historical sites [8], VirBELA provides a virtual collaborative environment for learners around the world [9], and platforms such as ClassVR, Engage, and Labster support virtual experiments and interactive learning in multiple disciplines [10–12]. At the same time, technology giants such as NVIDIA and Meta are also promoting sustainable development of the educational metaverse through their technology ecosystems. NVIDIA's Omniverse provides support for precise simulations, and Meta has invested USD 150 million to promote virtual reality education [13–15]. It is estimated that by 2028, the global educational metaverse market will reach USD 43.35 billion, and the user scale is expected to exceed 104.6 million by 2030 [16,17]. In the field of education, more and more scholars are concerned about the ethical impacts and challenges brought about by the integration of artificial intelligence tools into the educational environment [18–20]. In the design industry, more and more designers are beginning to use metaverse technology for virtual creation and team collaboration [21,22]. However, research on the behavioral intentions of design learners in collaborating with AI in the educational metaverse is still relatively limited. Therefore, this study aims to explore the key factors that affect the behavioral intentions of design learners by constructing the concept of a Human-AI collaboration platform in the educational metaverse (EMH-AIc). This will not only help optimize the collaborative experience of design learners and AI but also promote design education toward a more equitable, personalized, and sustainable development direction.

This study proposes that human and artificial intelligence collaboration in the educational metaverse (EMH-AIc) can serve as an effective path for design learners to overcome the limitations of the real world and carry out complex design collaboration. EMH-AIc is defined as a platform which allows design learners to interact and collaborate with AI technology in a virtual educational metaverse, thereby improving the learning experience, collaboration efficiency, and creativity [23–26]. Its specific operating mechanisms include the following. (1) Through high-precision modeling and AI algorithms, design tools and processes are transformed into interactive virtual models to achieve digital twins. (2) Two-way data flow and real-time feedback between the virtual design environment and AI tools are achieved so that learners can obtain intelligent design suggestions. (3) Learners manipulate virtual design projects in real time, and AI technology automatically generates and optimizes design solutions, providing personalized creative experiences and enhancing collaboration efficiency.

UNESCO emphasizes that learners' behavioral intention plays an important role in promoting global education goals [27]. Current research on behavioral intentions in the educational metaverse has mostly focused on basic frameworks such as the technology acceptance model (TAM), focusing on fundamental factors such as usability and ease of use [28]. However, these studies often ignore the key factors at the social and cognitive levels which influence the behavioral intentions of learners in complex virtual learning environments. Therefore, based on social cognitive theory (SCT) in social psychology and education, this study includes the perspective of human-AI collaboration for the first time and proposes a comprehensive behavioral model covering the external environment, individual cognition, and behavioral intention to fill the current research gap in the multi-dimensional understanding of behavioral intention. SCT believes that individual behavior is the result of the joint action of the external environment and personal cognition. Especially in complex learning situations, individuals need to adjust their behavior through processes such as correctly judging their own abilities, predicting the results of actions, and evaluating social opportunities and constraints [29,30]. This study integrates social and cognitive perspectives to construct a more comprehensive behavioral intention model which not only expands the theoretical framework of behavioral intention but also provides an application reference for design education practice in the educational metaverse and lays a theoretical foundation for sustainable development of the educational metaverse in the field of design education.

This research team aims to identify and analyze the key factors which influence design learners' use of EMH-AIc and provide practical guidance and suggestions for the design and operation of the educational metaverse. By revealing these key factors, this study not only helps the educational metaverse platform attract and retain design learners but also strives to promote lifelong learning and reduce educational inequality. Based on the SCT analysis framework, this study raises three core research questions: (1) What factors influence users' use of EMH-AIc? (2) How do these factors affect users' behavioral intentions? (3) Finally, do these factors promote the development of EMH-AIc? Answering these questions will provide the necessary theoretical and practical support for the continued development of EMH-AIc.

This study is structured as follows. Section 2 discusses the literature review and theoretical background related to EMH-AIc, aiming to lay an academic foundation for the study. Section 3 proposes research hypotheses based on SCT and analyzes the various factors which affect the behavioral intentions of design learners. Section 4 introduces the research methods, including detailed descriptions of the sample selection, questionnaire design, and data collection methods. Section 5 presents the research results, covering the reliability and validity tests of the model and analysis of the hypothesis testing. Section 6 discusses the results of the empirical study and evaluates their impact at the theoretical and practical levels. Section 7 points out the limitations of this study and proposes suggestions for future research directions. Finally, Section 8 summarizes the study. This study strictly followed academic standards to ensure the scientific, validity, and repeatability of the research methods.

## 2. Theoretical Background and Literature Review

### *2.1. Human-AI Collaboration in the Educational Metaverse as a Catalyst for Innovation in Design Education*

The formation of the educational metaverse stems from the both the drive of technological innovation and the need for educational equity. In 2003, the advent of the Second Life virtual world platform marked the prototype of the educational metaverse. Through an immersive virtual environment, the platform enables users to participate in social, learning, and creative activities in the form of virtual characters and has taken the lead in exploring virtual classrooms, interdisciplinary cooperation, and resource sharing, laying the foundation for future development of the educational metaverse [31,32]. With the rapid development of virtual reality (VR), augmented reality (AR), and artificial intelligence (AI) technologies, the educational metaverse has gradually become an important experimental field for exploring innovative educational models [33].

The introduction of artificial intelligence (AI), especially in personalized learning and real-time interaction, has greatly promoted teaching innovation in the educational metaverse. For example, intelligent learning management systems (LMSs) can use AI algorithms to recommend personalized learning paths for students [34], and natural language processing (NLP) technology supports real-time interaction and question-answering between virtual tutors and students [35,36]. In addition, deep learning technology helps predict students' learning outcomes by analyzing student data and provides teachers with timely strategy adjustment suggestions [37,38]. The application of these technologies not only improves teaching efficiency in the educational metaverse, but also greatly enhances the personalized learning experience [39].

At the same time, AI technology also plays an important role in promoting educational equity, especially in expanding the accessibility of educational resources and narrowing regional educational gaps. For example, online learning platforms such as Coursera and edX use AI technology to provide learners around the world with personalized learning suggestions and automated feedback, enabling students in remote areas to obtain the same quality of educational resources as urban students, thereby effectively narrowing the regional educational gap [40,41].

In design education, the application of AI technology has become a key factor in improving learning outcomes. Through machine learning and deep learning, AI can conduct in-depth analysis of learners' design works and generate personalized design suggestions, thereby helping students optimize the creative process and improve their creative efficiency and work quality [42,43]. For example, Autodesk's Dreamcatcher helps learners explore innovative design solutions and inspire their design inspiration by providing a variety of design options [44]. Similarly, AI design tools such as Adobe Sensei can analyze students' design styles and automatically recommend suggestions, such as color matching and layout adjustments, to help students further improve the expressiveness of their works [45]. These tools not only help students improve their creative efficiency but also enhance their understanding and control of the design process. Studies have shown that AI-assisted learning models can effectively improve learners' participation and learning interest [46]. He et al.'s study introduced AI technology into the traditional teaching system and found that after AI assistance, the creative level and production ability of design students were significantly improved [47]. In addition, the control group experiment of Huang's team further proved that the educational model combining AI technology with the educational metaverse can stimulate learners' enthusiasm more than using AI technology alone. This shows the importance of collaboration between AI and the educational metaverse in promoting innovation in design education.

The synergy between the educational metaverse and AI has brought unprecedented innovation opportunities to design education [48]. AI-generated content (AIGC) has rapidly become one of the key technologies in design education. It can provide personalized creative support based on students' design styles, greatly improving design efficiency. Pan et al. proposed a solution for AI-assisted design work. Students can use AI to achieve intelligent creation in the metaverse, significantly improving the efficiency and creative expression of the design process [49]. Yang et al.'s team verified the impact of the metaverse virtual environment on art design students through a case study method. The results showed that this intelligent collaboration model can significantly improve students' learning outcomes, further proving the potential for wide application of AI and educational metaverse collaboration in design education [50].

Previous studies mostly relied on the technology acceptance model (TAM) or the unified theory of acceptance and use of technology (UTAUT) to evaluate users' acceptance of the educational metaverse, usually focusing on the relationship between perceived usefulness, ease of use, and intention to use [51–53]. For example, Wang et al. explored the intention to use the metaverse platform in the education field based on the TAM model [54], while AlHamad and Akour et al. also conducted similar research on the application of the metaverse platform in higher education, analyzing the impact of technical factors on user intention [55,56]. In addition, Teng et al. extended the UTAUT model to examine learners' willingness to adopt and continue to use the educational metaverse, further explaining the relationship between technology acceptance and behavioral intention [57]. At the same time, the Samed team focused on the behavioral characteristics of Generation Z students in using the educational metaverse, pointing out the unique psychological and behavioral characteristics of this generation in technology acceptance and continued use [58].

Although these studies revealed the importance of technology in promoting development of the educational metaverse, their limitation is that most studies mainly explored users' behavioral intentions from a technical perspective, focusing on individuals' functional perceptions of technology and rarely considering the comprehensive effects of social and cognitive factors on behavior. In the context of AI collaboration in the educational metaverse, learners' behavior is not only affected by technology acceptance but also driven by social influence, self-efficacy, and outcome expectations. Unlike the "acceptance intention" focused on by the TAM and UTAUT, SCT provides a more comprehensive framework which can cover complex factors such as learners' social interaction, individual cognitive regulation, and situational dynamics, which are particularly critical in the context of design education. In particular, in the scenario of AI and design learners collaborating, social cognitive factors are particularly important for understanding learners' continued use intentions and behavioral adjustments, because AI collaboration in design education requires learners to be able to continuously adapt, reflect, and adjust in practice.

Therefore, based on social cognitive theory (SCT), this study aims to fill the gaps in existing research by analyzing key social cognitive factors such as social influence, self-efficacy, and outcome expectations and exploring how these factors jointly influence learners' behavioral intentions in the educational metaverse, where AI and design learners collaborate. The adoption of SCT not only fills the social cognitive gap that the TAM and UTAUT cannot fully explain but also provides a theoretical basis for optimizing the collaboration between AI and learners. This study will lay the foundation for further development of the educational metaverse in design education, making it more in line with learners' social cognitive needs in practice and supporting a more personalized and continuous learning experience.

### *2.2. Social Cognitive Theory (SCT)*

Social cognitive theory (SCT) was proposed by Albert Bandura. It emphasizes that individual behavior, personal cognition, and the external environment interact through "triadic reciprocal determinism" (TRD) to jointly determine individual behavioral choices [59,60]. The core idea of SCT is that individuals gradually form cognition of their own abilities and anticipate the results of future behaviors by observing the behavior of others, social interactions, and situational feedback [61]. Different from traditional passive user behavior theories, SCT provides a dynamic framework which explains how individuals actively make behavioral choices through the interaction of cognition and the external environment [62]. Therefore, based on SCT, this study aims to analyze and design learners' behavioral intentions and promote sustainable development of the educational metaverse, especially in the context of human-AI collaboration.

In recent years, the application of SCT in virtual environments has become increasingly widespread, covering multiple research fields. For example, in the field of healthcare, researchers have constructed an SCT framework which includes environmental dimensions (subjective norms and trust), personal dimensions (motivation and self-efficacy), and behavioral dimensions (behavioral intention) to analyze users' willingness to use remote virtual medical services [63]. In the field of online games, SCT has been used to analyze the impact of factors such as social support and emotional commitment on user loyalty [64], as well as explain users' motivation to watch live games [65]. In the field of education, Stuart's research showed that improving teachers' self-efficacy significantly increased students' intention to use AI technology [66]. In addition, Wijiaya explored the innovative behavior of primary school mathematics teachers and found that promoting conditions and self-efficacy had a direct impact on behavior [67]. Almulla's research evaluated the application of SCT in online education and analyzed the impact of contextual factors on students' learning behavior [68]. In addition, SCT is also widely used to construct teaching strategies to improve teaching effectiveness [69].

Although social cognitive theory (SCT) has been widely used in virtual learning environments, revealing the mechanism by which the external environment (such as technical support and teacher feedback) and personal cognition (such as self-efficacy and outcome expectations) jointly influence user behavior, these studies provide a solid theoretical basis for this study, especially in the analysis of behavioral intentions in designing learners' collaboration with AI. However, in the emerging field of the educational metaverse, systematic research on designing learners' collaboration with AI is still relatively insufficient.

For example, Amany's study explored the intention to use distance education platforms but did not conduct an in-depth analysis of specific educational fields [70]. Abeer focused on the behavioral intention of art students in mobile learning. However, the functions of the mobile learning system in his study were relatively basic, including only support functions such as PowerPoint display, homework, and testing and lacking research on more complex collaborative and interactive functions [71]. Although these studies provide a preliminary background for the application of SCT, there is still a large gap in the systematic analysis of the educational metaverse environment designed for learners to collaborate with AI.

Therefore, this study will explore the behavioral intentions of design learners to collaborate with AI in the educational metaverse based on the three-dimensional structure of SCT (external environment, individual cognition, and personal behavior). The research will focus on analyzing the impact of key variables such as social influence, rewards, teacher support, facilitation, self-efficacy, outcome expectations, and trust on the behavioral choices of design learners. By filling the gaps in the existing literature, this study not only aims to optimize the model of collaboration between AI and learners but also provide theoretical support for the development of the educational metaverse and promote the sustainable development of design education.

## 3. Hypothesis Development

### 3.1. The Direct Influence of the External Environment on Individual Behavior

The direct influence of the external environment on individual behavior has been validated across multiple theoretical frameworks, including social exchange theory (SET), social cognitive theory (SCT), and the theory of planned behavior (TPB) [72–74]. These frameworks collectively emphasize that behavior is shaped not only by internal cognitive factors but also by strong external environmental influences. Previous studies have confirmed that the external environment plays a crucial role in shaping the behavioral intentions of both teachers and students [75,76]. Given this understanding, it is essential to explore how external factors directly influence the behavioral intentions of design learners in virtual learning environments, particularly in the context of AI collaboration. In this study, the external environment consists of four major elements: social influence, rewards, teacher support, and facilitating conditions. Social influence is defined as the impact of others' opinions or behaviors (such as peers, teachers, or social groups) on learners, including encouragement, feedback, and recognition. Research by Salloum et al. and Lakhal et al. confirmed that social influence positively affects the intention to use e-learning systems within the UTAUT framework [77,78]. Rewards refer to material or non-material incentives, such as prizes, badges, or points. According to social exchange theory, individuals tend to make behavioral choices based on potential rewards or benefits [79]. Saranya et al. demonstrated that user behaviors, such as writing online reviews, increased significantly when driven by rewards [80]. Teacher support is another critical factor, defined as guidance and feedback provided by teachers to help learners collaborate with AI on design tasks within the educational metaverse. Granziera et al.'s cross-national research found that teacher support significantly boosts students' academic motivation and behavioral intentions [81]. Sakiz's findings further support the positive impact of teacher support on behavioral intention [82]. Finally, facilitating conditions refer to the availability of resources and technological support for learners to engage with AI within the educational metaverse. Nikou et al. demonstrated that the availability of devices and platform usability greatly affect learners' usage intentions in mobile learning systems [83]. Based on these insights, this study empirically investigates how these external environmental factors impact design learners' behavioral intentions to use the EMH-AIc platform and proposes the following hypotheses:

**H1.** *Social influence positively affects the behavioral intention of design learners to use EMH-AIc.*

**H2.** *Rewards positively affect the behavioral intention of design learners to use EMH-AIc.*

**H3.** *Teacher support positively affects the behavioral intention of design learners to use EMH-AIc.*

**H4.** *Facilitating conditions positively affect the behavioral intention of design learners to use EMH-AIc.*

*3.2. The Influence of the External Environment on Individual Cognition*

After being influenced by the external environment, learners usually make psychological and cognitive assessments to determine whether the environment is conducive to their learning and development [84,85]. The individual cognitive dimensions in this study include three main factors: self-efficacy, outcome expectations, and trust. Self-efficacy in this study refers to the confidence of design learners in their ability to successfully collaborate with AI technology to complete design tasks in the virtual educational metaverse. Outcome expectations are defined as the expectations of design learners for the results which can be obtained by using the AI collaboration platform, including whether it can improve design capabilities and learning outcomes. Trust refers to learners' trust in the educational metaverse platform, especially in terms of collaboration support, privacy protection, and data security. These factors represent the confidence of design learners in collaborating with AI technology to complete design tasks in the virtual educational metaverse (EMH-AIc), their expectations for the expected results of the collaboration platform, and their trust in the platform.

Social influence plays an important role in improving learners' self-efficacy, outcome expectations, and trust [63,86]. According to Bandura's social cognitive theory, positive feedback and support from others can significantly enhance an individual's self-efficacy [87]. In the educational metaverse, when learners observe their peers and mentors' positive comments on and frequent use of the platform, their self-confidence will increase, and they will be more inclined to believe they can successfully use the platform. In addition, motivation theory points out that learners' behaviors and expectations are often influenced by the feedback of others. When they observe that others have achieved significant learning results through the platform, their outcome expectations will also increase [85]. Trust, as the basis for users to continue to use the platform, will be enhanced by positive demonstrations of social influence [88]. When learners see that their peers and mentors have a high degree of recognition of the platform, they will have more confidence in the security and reliability of the platform. Based on this, this study proposes the following hypothesis:

**H5.** *Social influence has a positive impact on design learners' self-efficacy (H5a), outcome expectations (H5b), and trust (H5c) in using EMH-AIc.*

As an external motivational factor, rewards have a significant impact on learners' self-efficacy, outcome expectations, and trust. Self-determination theory shows that rewards can not only stimulate learners' intrinsic motivation but also convey affirmation of their abilities, thereby enhancing their self-efficacy [89]. At the same time, the reward mechanism increases learners' attention to the platform, making them pay more attention to the potential benefits brought by the platform, thereby improving their outcome expectations [90]. In addition, rewards can also serve as the platform's recognition of users' positive behaviors and enhance users' trust. Studies have shown that when learners receive reward feedback from the platform, they are more likely to believe that the platform recognizes the value of their behavior, thereby enhancing their trust in the platform [91,92]. Based on this, this study proposes the following hypothesis:

**H6.** *Rewards have a positive impact on design learners' self-efficacy (H6a), outcome expectations (H6b), and trust (H6c) in using EMH-AIc.*

Teacher support can effectively enhance learners' self-efficacy, outcome expectations, and trust by providing professional guidance and emotional support. As knowledge authorities, teachers can help learners overcome their fear of AI technology, improve their self-confidence, and make them believe that they can successfully use the platform [93,94]. In addition, teachers can help students understand the advantages of the platform more clearly through demonstration and guidance, thereby improving their outcome expectations. Teachers' recommendations and recognition also tend to enhance students' trust in the platform, especially in terms of data security and privacy protection [95,96]. Based on this, this study proposes the following hypothesis:

**H7.** *Teacher support has a positive impact on design learners' self-efficacy (H7a), outcome expectations (H7b), and trust (H7c) in using EMH-AIC.*

Convenience can provide technical support and resource guarantees, which can significantly improve their self-efficacy, outcome expectations, and trust [97]. Convenience helps learners overcome technical barriers by reducing the difficulty of using the platform, making them more confident in their ability to use it. Convenient usage conditions not only reduce the operational burden of learners but also make them more expectant of the platform's effects. In addition, the provision of convenience enhances the reliability of the platform, thereby enhancing learners' trust in the platform and making them more willing to use the platform in the long term [98]. Based on this, this study proposes the following hypothesis:

**H8.** *Facilitating conditions have a positive impact on design learners' self-efficacy (H8a), outcome expectations (H8b), and trust (H8c) in using EMH-AIc.*

### *3.3. The Direct Impact of Individual Cognition on Individual Behavior*

Based on the theory of reasoned action (TRA), individual behavior is shaped by attitudes toward the behavior, beliefs regarding the behavioral outcomes, and evaluations of those outcomes [99]. Within this framework, learners' cognitive assessments play a pivotal role in forming their behavioral intentions. As learners are influenced by external factors, such as social influence, rewards, teacher support, and facilitating conditions, they integrate these external inputs with internal cognitive factors like self-efficacy, outcome expectations, and trust to form a clear intention to engage in specific behaviors. In this study, behavioral intention refers to whether design learners, after being exposed to these external factors and engaging in cognitive evaluations, are inclined to collaborate with AI in the educational metaverse to complete design tasks. Previous research highlights that self-efficacy, outcome expectations, and trust are key cognitive factors influencing behavioral intention. For instance, high self-efficacy is linked to stronger learning motivation and a greater willingness to tackle complex tasks within virtual learning environments [63]. Similarly, when learners hold high expectations about the outcomes of using a specific technology, such as believing it will enhance their learning or design skills, their intention to engage with the platform significantly increases [100]. Trust is also critical; learners who have confidence in the reliability and security of a virtual platform, including its AI functionalities, are more likely to engage deeply with the system [101]. Based on this, this study will empirically test the direct impact of the three cognitive factors of self-efficacy, outcome expectations, and trust on design learners' behavioral intentions to use EMH-AIc. Based on the above analysis, the following hypotheses are proposed:

**H9.** *Self-efficacy positively influences design learners' behavioral intentions to use EMH-AIc.*

**H10.** *Outcome expectations positively influence design learners' behavioral intentions to use EMH-AIc.*

**H11.** *Trust positively influences design learners' behavioral intentions to use EMH-AIc.*

### *3.4. Proposed Research Model*

This study developed a multidimensional conceptual model based on social cognitive theory (SCT), integrating social exchange theory and planned behavior theory to explore the impact of external environment factors (such as social influence, rewards, teacher support, and facilitating conditions) on cognitive factors and behavioral intention. The model aims to provide a theoretical basis for optimizing the educational metaverse platform, promoting educational equity, and enhancing learners' AI collaboration experiences.

## 4. Research Methods

### *4.1. Questionnaire Development*

The research model is composed of eight key variables: social influence (SIE), rewards (RW), teacher support (TS), facilitating conditions (FC), self-efficacy (SE), outcome expectations (OE), trust (TRU), and behavioral intention (BI). Each of these variables has been adapted from previously validated scales in the literature to ensure their relevance in the context of the educational metaverse for human-AI collaboration (EMH-AIc). SIE items were adapted by Nikou et al.'s study [83,102,103]. RW items were modified based on Cui et al.'s study [80,104,105]. TS items were derived from Adela et al.'s study [106–109]. FC items were adapted according to Ain et al.'s study [83,97,110]. SE items were modified following Shahangian et al.'s study [63,75,86,103,111]. OE items were adjusted based on the research by Rana et al. [86,100,103,111]. TRU items were adapted from Wu et al.'s study [63,112]. BI items were based on Li et al.'s study [63,83,102,103,110]. Details of the survey items related to these variables are provided in Appendix A. Each item in the questionnaire was measured using a 5 point Likert scale, ranging from "strongly disagree (1)" to "strongly agree (5)".

Before initiating the survey, three professional translators with extensive experience reviewed the questionnaire to ensure that the content was clear and free from translation errors which could cause misunderstandings. Additionally, three professors specializing in education and two industry experts examined the content of the questionnaire to ensure its reliability and validity.

The questionnaire aims to evaluate participants' initial reactions and usage intentions after experiencing the EMH-AIc platform, helping us assess their likelihood of adopting such platforms [113]. Selecting the appropriate platform was critical, and after careful consideration of EMH-AIc's unique characteristics, we chose the Apache Art Studio on Spatial.io as the experimental platform (Figure 1). This decision was driven by several key factors:

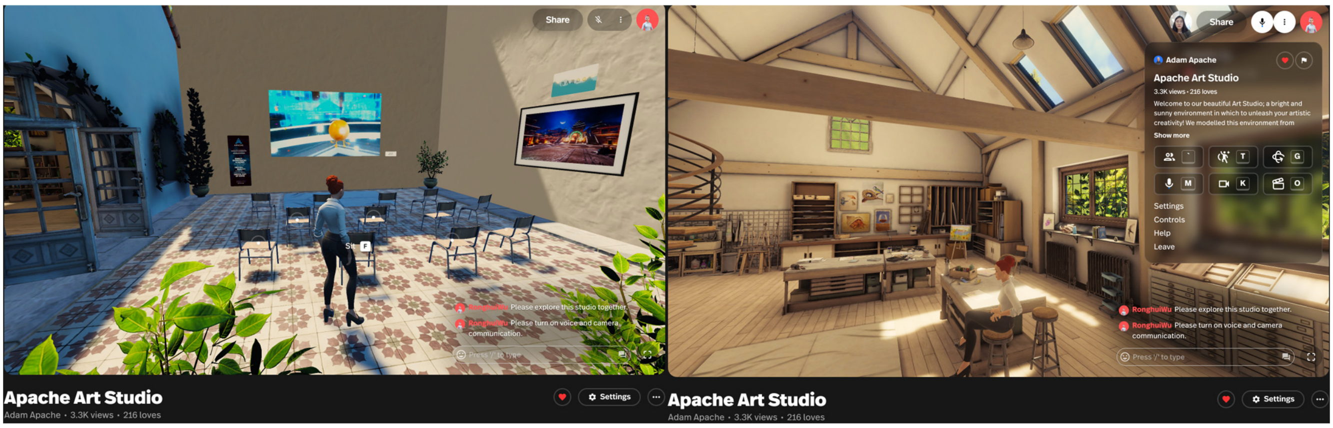


**Figure 1.** Apache Art Studio user experience and practical scenarios.

- Accessibility and User Engagement: Spatial is browser-based, requiring no extensive setup or VR hardware. This feature is particularly valuable in educational research, as it allows participants from diverse backgrounds, including art professionals and students, to easily access the platform, thus lowering the technical barrier.
- Real-time Collaboration: Spatial supports interactive real-time collaboration, a key element in studying human-AI collaboration. Users can upload digital artwork, interact with 3D objects, and co-create in shared spaces, making it an ideal environment for exploring collaborative processes between human users and AI-driven tools.

- Creative and Artistic Applications: Apache Art Studio emphasizes art and creative exploration, aligning with the needs of design learners and professionals. The platform allows users to showcase, manipulate, and engage with artistic content, providing a practical environment to study how AI can assist or enhance the creative process in educational and artistic contexts.
- Integration of AI Tools: While Spatial focuses on user-generated content, it has the potential to integrate AI-driven content creation and curation tools. This makes it an excellent environment for studying how AI can assist or enhance human creativity in educational or professional artistic settings. For instance, users can explore how AI helps curate virtual exhibitions, generate artistic assets, or facilitate cross-cultural collaboration among artists.
- Multimodal Learning Environment: Spatial provides an immersive, multimodal environment combining audio, visual, and interactive elements. This set-up supports the integration of AI technologies into a rich learning ecosystem, encouraging not only artistic exploration but also educational activities like workshops or collaborative design sessions.

### *4.2. Data Collection and Analysis*

This study aims to explore design learners' cognitive evaluations when using the educational metaverse for human-AI collaboration (EMH-AIc) and how these evaluations influence their behavioral intentions. The focus is on how four external factors—social influence, rewards, teacher support, and facilitating conditions—drive design learners' willingness to use the EMH-AIc platform by influencing their self-efficacy, outcome expectations, and trust. To validate the research model, an online anonymous survey was conducted using snowball sampling [114].

Snowball sampling is an efficient way to reach a specific and concentrated target group. It is particularly suitable for the subjects of this study, namely design learners, especially those who are familiar with the metaverse and AI collaboration tools [115]. This group accounts for a small proportion of the total population and is concentrated in specific design schools. Therefore, we launched the first round of questionnaire invitations among design students from three top design schools in China and spread them through their social networks to obtain effective samples which met the research needs. This method not only improved the efficiency and pertinence of data collection but also ensured that the sample was highly representative of the target group. However, the limitation of snowball sampling is that it may introduce sample homogeneity bias and selection bias. Since the respondents mainly came from schools and majors with similar backgrounds, the behaviors and attitudes of the respondents may have been relatively consistent, thus limiting the diversity of the sample. In addition, expanding the sample through social networks may have led to the exclusion of some individuals who had not been exposed to the network, further affecting the representativeness of the sample. In order to minimize the impact of these biases on the research conclusions, we strictly explained the group characteristics of the sample in the data analysis and discussion and made it clear that it had a certain degree of concentration characteristics to avoid over-generalization of the research conclusions. In addition, the individual characteristics of the sample were recorded in detail and considered in the analysis to increase the broad applicability and rigor of the findings. Although snowball sampling has its limitations, we took scientific control measures to ensure the credibility and explanatory power of the conclusions of this study in the design education context.

The survey was divided into two parts. The first part required participants to experience the EMH-AIc platform, ensuring they were familiar with its features and functionality before answering the questionnaire. For this, each participant was provided with a detailed user guide and access link, directing them to the virtual space within Apache Art Studio on the Spatial.io platform. There, participants engaged in design creation and collaboration in a metaverse environment. This virtual space allowed users to explore with digital avatars, participate in interactive discussions via video, voice, or text, upload design projects, and collaborate with AI tools. Each participant was asked to spend a minimum of 15 min on the platform to ensure sufficient depth and breadth of the experience. The platform was accessible on Windows, macOS, iOS, and Android systems, allowing participants to collaborate in real time using virtual tools. After completing the experience in Apache Art Studio, the participants proceeded to the second part of the questionnaire. To ensure data accuracy, all participants were required to complete both the EMH-AIc experience and the questionnaire on the same day, minimizing any potential impact of memory recall on the accuracy of their responses.

A total of 550 questionnaires were collected for this study. After reviewing the responses, 17 were excluded due to uniform or invalid answers, leaving 533 valid samples for data analysis. Table 1 provides the demographic characteristics of the respondents. Males accounted for 58.30% (311 individuals) of the respondents, while females made up 41.70% (222 individuals). In terms of age distribution, the majority of the participants fell within the 18–29 age group (74.11%) followed by those aged 30–39 (21.01%), with fewer respondents aged 40 and above (4.88%). This distribution reflects the typical age structure of the design learner group, among which those aged 18–29 are in the early stages of university study and career development. Learners at this stage are usually more receptive to emerging technologies and more actively seek to combine technology with learning, especially in the field of design. The proportion of learners between 30 and 39 was also considerable, indicating that some learners still chose to continue learning or improve their design skills through new technical means after working for several years. This may also reflect their need for career advancement and skill updating. The proportion of learners aged 40 and above was relatively low, which may be related to the fact that design practitioners in this age group have been relatively stable in their career development, or their interest in and acceptance of new technologies are relatively low. Therefore, the distribution of this survey result is consistent with the learning motivation and behavioral characteristics of different age groups in the process of design education and career development.

**Table 1.** Demographics of participants (N = 533).

| Measure | Items | Frequency | Gender (Male) | Gender (Female) | Percentage (%) |
|---|---|---|---|---|---|
| Age | 18~29 | 395 | 230 | 165 | 74.11 |
| | 30–39 | 112 | 66 | 46 | 21.01 |
| | 40 and above | 26 | 15 | 11 | 4.88 |
| Education [1] | Less than undergraduate | 60 | 36 | 24 | 11.30 |
| | Undergraduate | 329 | 189 | 140 | 61.70 |
| | Post-graduate | 104 | 59 | 45 | 19.50 |
| | Doctor | 40 | 27 | 13 | 7.50 |
| Major [2] | Graphic design or visual communication design | 60 | 34 | 26 | 11.30 |
| | Industrial design or product design | 105 | 63 | 42 | 19.70 |
| | Interaction design user experience design | 60 | 32 | 28 | 11.30 |
| | Environmental design | 70 | 45 | 25 | 13.10 |
| | Fashion design | 59 | 36 | 23 | 11.10 |
| | Digital media design | 93 | 50 | 43 | 17.40 |
| | Service design | 31 | 18 | 13 | 5.80 |
| | Social innovation design | 13 | 8 | 5 | 2.40 |
| | Emerging technology and design | 42 | 25 | 17 | 7.90 |
| Usage frequency | 1–2 times per month | 49 | 25 | 24 | 9.20 |
| | 3–4 times per month | 103 | 50 | 53 | 19.30 |
| | 1–2 times per week | 200 | 122 | 78 | 37.50 |
| | 3–5 times per week | 123 | 78 | 45 | 23.10 |
| | Daily | 58 | 36 | 22 | 10.90 |
| Context dependence [3] | Only used in class | 82 | 42 | 40 | 15.40 |
| | Occasionally used outside class | 235 | 141 | 94 | 44.10 |
| | Frequently used for both class and non-class activities | 165 | 102 | 63 | 30.90 |
| | Used every day for learning or collaboration | 51 | 26 | 25 | 9.60 |
| | Total participants | 533 | 311 | 222 | 100.0 |

[1] The measure of education includes graduated and currently enrolled. [2] Choose similar option if major names differ. [3] Motivation and scenarios.

In terms of educational background, the majority of the respondents were undergraduate students (61.70%), followed by graduate students (19.50%), and doctoral students (7.50%). This indicates that most respondents were in the early stages of their educational or career development, with a significant portion pursuing advanced degrees, which may explain their greater exposure to educational technologies like the metaverse. It is worth noting that there were relatively more male undergraduates, which may be related to the fact that some technology-oriented design majors (such as industrial design) have more male participants. Regarding professional focus, participants specializing in industrial design or product design (19.70%) and digital media design (17.40%) were represented the most. This suggests that these fields have a higher demand for technological integration, particularly in AI collaboration during the design process, making these learners more inclined to use platforms like EMH-AIc. As for platform usage frequency, 37.50% of the participants reported using the platform 1–2 times per week, while 23.10% used it 3–5 times per week. Although a significant portion of design learners use the platform regularly, it has not yet become a daily tool for most. Additionally, 44.10% of the respondents stated they occasionally used it outside of class, while 31% used it frequently for both classroom and extracurricular activities. This reflects the flexibility and wide applicability of the educational metaverse platform in both formal learning environments and self-directed collaboration.

This study used partial least squares structural equation modeling (PLS-SEM) to evaluate the research model and verified the validity of the measurement model and structural model through SPSS 27.0 and SmartPLS 4.0. PLS-SEM is gradually gaining attention in the study of user experience and behavioral intention in the context of the metaverse due to its advantages in predicting dependent variables and explaining the relationship between independent variables [116–118]. In addition, since PLS shows strong robustness and accuracy in the case of small sample data, it is particularly suitable for the data collected in this study [119].

## 5. Results

All variables in this study were collected through the same questionnaire, and thus the common method variance (CMV) was tested in the first step of statistical analysis to eliminate potential bias problems. Harman's one-factor test was used to evaluate the CMV, and factor analysis was performed on all items in the model using IBM SPSS Statistics 27.0. A total of eight factors were extracted in this study, and the first factor explained 28.58% of the variance, which was less than 50%. Therefore, the data in this study did not have significant common method variance problems [120].

### *5.1. Measurement Model*

To evaluate the model fit in this study, we used the standardized root mean square residual (SRMR) and the normed fit index (NFI) as the primary indicators (Table 2). Model fit determines the accuracy and effectiveness of the model in explaining the data, making these metrics crucial in assessing model quality. The SRMR value was 0.047, indicating a good model fit. Typically, an SRMR value below 0.08 is considered an acceptable fit, and values under 0.05 often suggest an excellent fit between the model and actual data [119]. Therefore, this study's model demonstrated a strong fit with minimal data error, suggesting that it reasonably explained the relationships between the variables. The NFI, used to compare model fit with a null model, approaches one when the fit is good [121]. In this study, the NFI value was 0.866, further indicating a relatively strong fit for the model.

**Table 2.** Model fit.

| Fit Index | Computed Values | Threshold Reference |
| --- | --- | --- |
| SRMR | 0.047 | [119] |
| NFI | 0.866 | [121] |

In the partial least squares structural equation modeling (PLS-SEM) analysis, we primarily examined the reliability, internal consistency reliability, convergent validity, and discriminant validity of the measurement indicators. Factor loadings indicate how well a measurement variable reflects the information of the latent variable, with higher values (closer to one) suggesting stronger representation. As shown in Appendix A and Table 3, all factor loadings for the measurement variables were above 0.7, with the factor loadings for the structural elements ranging from 0.788 to 0.88. These values confirm that the measurement model demonstrated a strong representation of the latent constructs, ensuring both the reliability and validity of the model.

**Table 3.** Factor loads and cross-loads.

| | BI | FC | OE | RW | SE | SIE | TRU | TS |
|---|---|---|---|---|---|---|---|---|
| BI1 | 0.808 | 0.262 | 0.244 | 0.33 | 0.356 | 0.225 | 0.375 | 0.276 |
| BI2 | 0.847 | 0.285 | 0.321 | 0.337 | 0.387 | 0.264 | 0.35 | 0.255 |
| BI3 | 0.833 | 0.354 | 0.257 | 0.272 | 0.378 | 0.269 | 0.366 | 0.288 |
| BI4 | 0.829 | 0.275 | 0.256 | 0.297 | 0.316 | 0.251 | 0.391 | 0.275 |
| FC1 | 0.275 | 0.845 | 0.181 | 0.249 | 0.322 | 0.275 | 0.339 | 0.241 |
| FC2 | 0.312 | 0.788 | 0.158 | 0.263 | 0.294 | 0.187 | 0.318 | 0.267 |
| FC3 | 0.296 | 0.826 | 0.182 | 0.215 | 0.297 | 0.202 | 0.311 | 0.262 |
| FC4 | 0.287 | 0.832 | 0.205 | 0.249 | 0.289 | 0.252 | 0.324 | 0.298 |
| OE1 | 0.29 | 0.195 | 0.856 | 0.233 | 0.261 | 0.207 | 0.282 | 0.181 |
| OE2 | 0.254 | 0.19 | 0.834 | 0.311 | 0.243 | 0.246 | 0.271 | 0.194 |
| OE3 | 0.305 | 0.19 | 0.847 | 0.317 | 0.292 | 0.241 | 0.306 | 0.23 |
| OE4 | 0.239 | 0.163 | 0.825 | 0.231 | 0.204 | 0.211 | 0.299 | 0.185 |
| RW1 | 0.317 | 0.239 | 0.258 | 0.83 | 0.295 | 0.233 | 0.328 | 0.23 |
| RW2 | 0.331 | 0.269 | 0.307 | 0.832 | 0.291 | 0.26 | 0.357 | 0.245 |
| RW3 | 0.296 | 0.216 | 0.256 | 0.837 | 0.272 | 0.238 | 0.343 | 0.225 |
| RW4 | 0.295 | 0.261 | 0.268 | 0.83 | 0.285 | 0.235 | 0.374 | 0.279 |
| SE1 | 0.366 | 0.316 | 0.26 | 0.328 | 0.838 | 0.245 | 0.269 | 0.291 |
| SE2 | 0.357 | 0.298 | 0.246 | 0.25 | 0.795 | 0.26 | 0.266 | 0.31 |
| SE3 | 0.31 | 0.282 | 0.239 | 0.265 | 0.802 | 0.256 | 0.256 | 0.294 |
| SE4 | 0.37 | 0.276 | 0.216 | 0.268 | 0.814 | 0.238 | 0.251 | 0.304 |
| SE5 | 0.361 | 0.313 | 0.262 | 0.287 | 0.823 | 0.238 | 0.245 | 0.279 |
| SIE1 | 0.282 | 0.24 | 0.249 | 0.245 | 0.235 | 0.812 | 0.263 | 0.198 |
| SIE2 | 0.18 | 0.23 | 0.167 | 0.21 | 0.234 | 0.809 | 0.295 | 0.236 |
| SIE3 | 0.231 | 0.206 | 0.224 | 0.213 | 0.236 | 0.819 | 0.253 | 0.208 |
| SIE4 | 0.287 | 0.231 | 0.232 | 0.272 | 0.28 | 0.816 | 0.26 | 0.204 |
| TRU1 | 0.356 | 0.295 | 0.263 | 0.327 | 0.253 | 0.272 | 0.798 | 0.225 |
| TRU2 | 0.382 | 0.327 | 0.294 | 0.359 | 0.269 | 0.307 | 0.844 | 0.234 |
| TRU3 | 0.358 | 0.336 | 0.308 | 0.352 | 0.256 | 0.276 | 0.84 | 0.243 |
| TRU4 | 0.387 | 0.346 | 0.28 | 0.362 | 0.273 | 0.237 | 0.843 | 0.287 |
| TS1 | 0.304 | 0.294 | 0.207 | 0.257 | 0.316 | 0.245 | 0.252 | 0.856 |
| TS2 | 0.295 | 0.297 | 0.201 | 0.299 | 0.344 | 0.214 | 0.276 | 0.88 |
| TS3 | 0.246 | 0.24 | 0.202 | 0.194 | 0.269 | 0.206 | 0.236 | 0.838 |

In this study, reliability and validity assessments of the variables were conducted using Cronbach's alpha and the composite reliability (CR) and average variance extracted (AVE) as key indicators (Table 4). Cronbach's alpha was employed to measure the internal consistency reliability of each variable. All variables showed a Cronbach's alpha value above 0.80, indicating strong internal consistency, with values ranging from 0.822 (TS) to 0.873 (SE). Composite reliability (CR) was also used to assess the reliability of the latent variables, as it provides a more accurate measure of consistency than Cronbach's alpha. All CR values exceeded 0.85, indicating high reliability, with CR values ranging from 0.887 (SIE) to 0.908 (SE). Finally, AVE was used to measure the convergent validity of each variable, with all AVE values above 0.50, indicating that each variable explained more than half of the variance in its indicators and thus meeting the standard for convergent validity [122]. The AVE values ranged from 0.662 (SIE) to 0.737 (TS), demonstrating good discriminant and convergent validity for each variable. Consequently, the reliability and validity assessments in this study meet the accepted standards, ensuring the robustness of the measurement model.

**Table 4.** Indicators of the reliability and validity of the concept.

| | CA | CR (rho_a) | CR (rho_c) | AVE |
|---|---|---|---|---|
| BI | 0.849 | 0.849 | 0.898 | 0.688 |
| FC | 0.841 | 0.841 | 0.894 | 0.677 |
| OE | 0.862 | 0.867 | 0.906 | 0.707 |
| RW | 0.852 | 0.853 | 0.9 | 0.692 |
| SE | 0.873 | 0.874 | 0.908 | 0.663 |
| SIE | 0.83 | 0.833 | 0.887 | 0.662 |
| TRU | 0.851 | 0.852 | 0.9 | 0.691 |
| TS | 0.822 | 0.827 | 0.893 | 0.737 |

Based on the discriminant validity analysis in Table 5, we compared the square roots of the AVE for each latent variable with the correlation coefficients between the latent variables. The bolded values along the diagonal represent the square root of the AVE for each latent variable, while the off-diagonal values are the correlation coefficients between the latent variables. To demonstrate discriminant validity in the model, the square root of the AVE for a given latent variable should be greater than its correlation coefficients with other latent variables. As can be seen in the table, all latent variables met this criterion. For instance, the square root of the AVE for behavioral intention (BI) was 0.829, higher than its correlation coefficients with other latent variables such as facilitating conditions (FC), outcome expectations (OE), and rewards (RW). Similarly, the square root of the AVE for self-efficacy (SE) was 0.814, exceeding its correlations with other variables. This indicates that each latent variable in the model possessed strong discriminant validity, meaning that each variable could be effectively distinguished from the others and had independent explanatory power. Therefore, from the perspective of discriminant validity, the measurement model in this study demonstrated a high capacity for differentiating between variables, meeting the requirements for structural equation modeling. This enhanced the reliability and validity of the model's results.

**Table 5.** Distinguishing validity (Fornell–Larcker criterion).

| | BI | FC | OE | RW | SE | SIE | TRU | TS |
|---|---|---|---|---|---|---|---|---|
| BI | **0.829** | | | | | | | |
| FC | 0.355 | **0.823** | | | | | | |
| OE | 0.326 | 0.221 | **0.841** | | | | | |
| RW | 0.373 | 0.297 | 0.328 | **0.832** | | | | |
| SE | 0.434 | 0.365 | 0.300 | 0.344 | **0.814** | | | |
| SIE | 0.305 | 0.279 | 0.27 | 0.291 | 0.304 | **0.814** | | |
| TRU | 0.446 | 0.393 | 0.344 | 0.421 | 0.316 | 0.328 | **0.831** | |
| TS | 0.330 | 0.325 | 0.237 | 0.295 | 0.363 | 0.259 | 0.298 | **0.858** |

In order to further ensure the discriminant validity of the model, we supplemented the Heterotrait:monotrait (HTMT) ratio analysis in addition to the Fornell–Larcker standard. The HTMT ratio is a more stringent discriminant validity assessment method which judges the discrimination between variables by comparing the average values of the heterogeneity and homogeneity relationships between latent variables. Generally, HTMT values below 0.85 or 0.90 indicate good discriminant validity [123,124].

In this study, we used the HTMT ratio to verify the independence between the latent variables (Table 6). The results showed that the HTMT values of all variable pairs were lower than 0.85, indicating that under stricter standards, the latent variables still had significant discriminant validity. Therefore, through the dual verification of the Fornell–Larcker standard and the HTMT ratio, the discriminant validity of the measurement model of this study was further supported, which enhanced the independence between the latent variables and the reliability and validity of the model results.

**Table 6.** Distinguishing validity (HTMT values).

| | BI | FC | OE | RW | SE | SIE | TRU | TS |
|---|---|---|---|---|---|---|---|---|
| BI | - | | | | | | | |
| FC | 0.42 | | | | | | | |
| OE | 0.378 | 0.258 | | | | | | |
| RW | 0.438 | 0.349 | 0.377 | | | | | |
| SE | 0.503 | 0.426 | 0.343 | 0.398 | | | | |
| SIE | 0.358 | 0.332 | 0.315 | 0.343 | 0.355 | | | |
| TRU | 0.526 | 0.464 | 0.402 | 0.494 | 0.367 | 0.392 | | |
| TS | 0.393 | 0.388 | 0.28 | 0.348 | 0.426 | 0.314 | 0.355 | - |

Table 7 shows the $R^2$, adjusted $R^2$, and $Q^2$ values of each latent variable in the model. The $R^2$ value indicates the explanatory power of the independent variable on the latent variable. Among them, BI (0.341), TRU (0.29), and SE (0.255) all reached a moderate level, indicating that the independent variables had a certain explanatory power for these latent variables. Although the $R^2$ value of OE was relatively low (0.159), it was still reasonable for exploratory research. The adjusted $R^2$ value was close to the $R^2$ value, indicating that the model had no obvious noise effect and had good explanatory stability. In addition, the $Q^2$ values of all latent variables were greater than zero, (For example, BI was 0.228, and TRU was 0.195) indicating that the model had effective predictive relevance. These results show that although the individual values were not high, the model as a whole had moderate explanatory power and predictive ability, supporting its applicability in measurement and structural models.

**Table 7.** Values of R2 and Q2.

| | $R^2$ | $R^2$ Adjusted | $Q^2$ |
|---|---|---|---|
| BI | 0.341 | 0.333 | 0.228 |
| OE | 0.159 | 0.152 | 0.107 |
| SE | 0.255 | 0.249 | 0.166 |
| TRU | 0.29 | 0.284 | 0.195 |

*5.2. Modeling Analysis*

The study's final model demonstrated robust reliability and validity, with variance inflation factor (VIF) values ranging between 1.626 and 2.206 across all indicators, indicating no multicollinearity issues [123–125]. This reliability in our constructs supports the validity of our path analyses, and it enhanced the interpretability of the findings. Our model testing, through bootstrapping (5000 iterations), confirmed the majority of the hypothesized relationships, validating the model's effectiveness in assessing factors influencing behavioral intentions in the EMH-AIc platform.

In the path relationship analysis of variables in Table 8 and Figure 2, H1 was not supported ($\beta = 0.063$, T value = 1.37, $p > 0.05$), indicating that social influence had no significant direct impact on behavioral intention. In contrast, suppose H2 ($\beta = 0.104$, T value = 2.334, $p < 0.05$), H3 ($\beta = 0.087$, T value = 2.012, $p < 0.05$) and H4 ($\beta = 0.093$, T value = 2.131, $p < 0.05$) were supported, indicating that rewards, teacher support, and convenient conditions have a significant positive impact on behavioral intentions. In addition, social influence had a significant positive impact on self-efficacy, outcome expectations, and trust, supporting hypotheses H5a ($\beta = 0.140$, T value = 3.036, $p < 0.05$), H5b ($\beta = 0.156$, T value = 3.335, $p < 0.05$), and H5c ($\beta = 0.156$, T value = 3.668, $p < 0.05$).

**Table 8.** Hypothesis testing and collinearity assessment results.

| Hypothesis | *β* | SD | T Value | *p* Value | Results |
|---|---|---|---|---|---|
| H1: SIE -> BI | 0.063 | 0.046 | 1.37 | 0.171 | Not supported |
| H2: RW -> BI | 0.104 | 0.044 | 2.334 | 0.02 | Supported |
| H3: TS -> BI | 0.087 | 0.043 | 2.012 | 0.044 | Supported |
| H4: FC -> BI | 0.093 | 0.043 | 2.131 | 0.033 | Supported |
| H5a: SIE -> SE | 0.140 | 0.046 | 3.036 | 0.002 | Supported |
| H5b: SIE -> OE | 0.156 | 0.047 | 3.335 | 0.001 | Supported |
| H5c: SIE -> TRU | 0.156 | 0.043 | 3.668 | 0 | Supported |
| H6a: RW -> SE | 0.181 | 0.046 | 3.921 | 0 | Supported |
| H6b: RW -> OE | 0.230 | 0.047 | 4.941 | 0 | Supported |
| H6c: RW -> TRU | 0.277 | 0.044 | 6.357 | 0 | Supported |
| H7a: TS -> SE | 0.206 | 0.048 | 4.321 | 0 | Supported |
| H7b: TS -> OE | 0.104 | 0.046 | 2.261 | 0.024 | Supported |
| H7c: TS -> TRU | 0.100 | 0.044 | 2.264 | 0.024 | Supported |
| H8a: FC -> SE | 0.206 | 0.048 | 4.277 | 0 | Supported |
| H8b: FC -> OE | 0.075 | 0.045 | 1.656 | 0.098 | Not supported |
| H8c: FC -> TRU | 0.235 | 0.046 | 5.143 | 0 | Supported |
| H9: SE -> BI | 0.216 | 0.049 | 4.401 | 0 | Supported |
| H10: OE -> BI | 0.093 | 0.045 | 2.059 | 0.04 | Supported |
| H11: TRU -> BI | 0.219 | 0.057 | 3.833 | 0 | Supported |

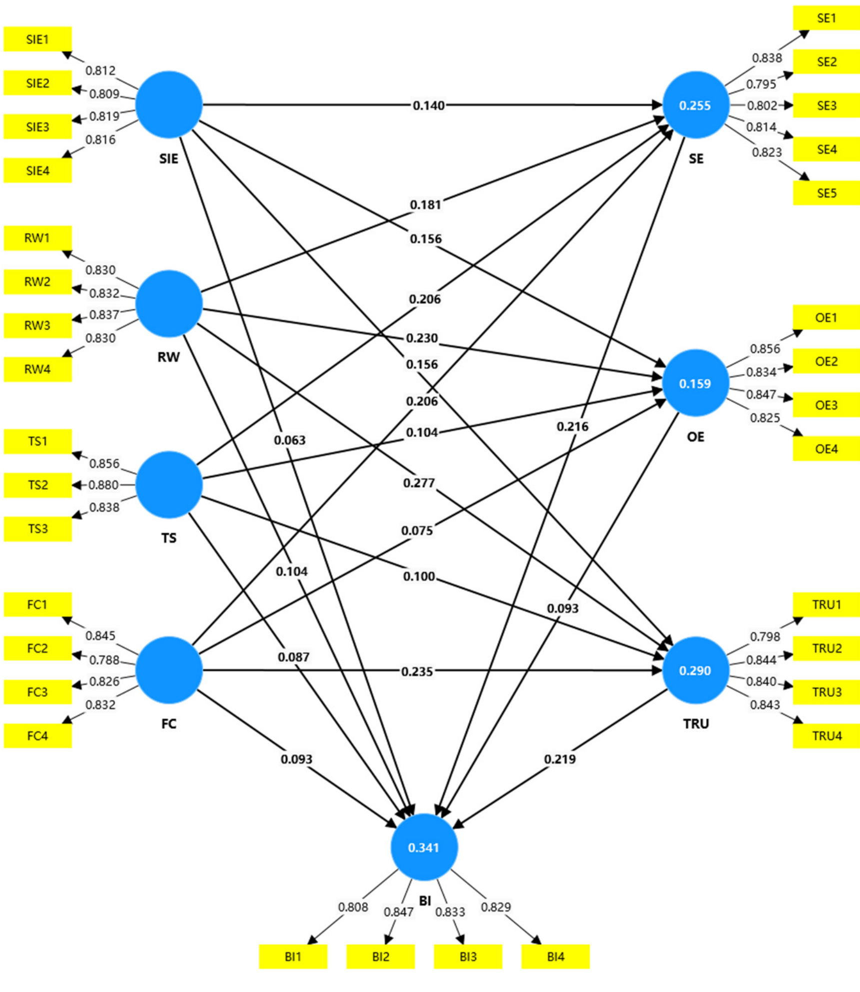


**Figure 2.** Results of PLS structural model.

Similarly, the effects of rewards on self-efficacy, outcome expectations, and trust were all significant, supporting hypotheses H6a (β = 0.181, T value = 3.921, $p < 0.05$), H6b (β = 0.230, T value = 4.941, $p < 0.05$), and H6c (β = 0.277, T value = 6.357, $p < 0.05$). The significant impact of teacher support on self-efficacy, outcome expectations, and trust support hypotheses H7a (β = 0.206, T value = 4.321, $p < 0.05$), H7b (β = 0.104, T value = 2.261,

$p < 0.05$), and H7c ($\beta = 0.1$, T value = 2.264, $p < 0.05$). Facilitating conditions had a significant impact on self-efficacy and trust (H8a supported, with $\beta = 0.206$ and T value = 4.277, $p < 0.05$; H8c supported, with $\beta = 0.235$ and T value = 5.143, $p < 0.05$), but the outcome expectations from the effect were not significant (H8b was not supported, with $\beta = 0.075$ and T value = 1.656, $p > 0.05$).

Finally, cognitive factors had a significant direct impact on behavioral intention, including self-efficacy (H9, $\beta = 0.216$, T value = 4.401, $p < 0.05$), outcome expectations (H10, $\beta = 0.093$, T value = 2.059, $p < 0.05$), and trust (H11, $\beta = 0.219$, T value = 3.833, $p < 0.05$), with all supporting the positive effect on behavioral intention.

### 5.3. Mediation Analysis

According to the analysis of the mediation effect results (Table 9), some external factors had a significant indirect effect on behavioral intention (BI) through self-efficacy (SE) and trust (TRU). The mediating effects of social influence (SIE) on BI through SE and TRU were 21.13% and 23.94%, respectively, indicating that when learners receive support from the social environment, this support can effectively enhance their self-efficacy and trust in the platform, thereby indirectly increasing their willingness to use the platform. Similarly, the mediating effect of rewards (RW) on BI through TRU reached 27.11%, indicating that an appropriate reward mechanism can further promote learners' acceptance and intention to use the platform by enhancing their sense of trust. These results emphasize the role of trust as a key mediating variable and verify the importance of trust in a complex technological environment.

**Table 9.** Mediation effect analysis: path coefficients, significance, and VAF values.

| Relationship | $\beta$ | SD | T Value | $p$ Value | 2.50% | 97.5% | Results | VAF |
|---|---|---|---|---|---|---|---|---|
| SIE -> SE -> BI | 0.03 | 0.012 | 2.468 | 0.014 | 0.009 | 0.058 | Significant Mediation | 21.13% |
| SIE -> OE -> BI | 0.014 | 0.008 | 1.77 | 0.077 | 0.001 | 0.033 | Non-Significant Mediation | 9.86% |
| SIE -> TRU -> BI | 0.034 | 0.013 | 2.57 | 0.01 | 0.013 | 0.065 | Significant Mediation | 23.94% |
| RW -> SE -> BI | 0.039 | 0.014 | 2.879 | 0.004 | 0.016 | 0.069 | Non-Significant Mediation | 17.33% |
| RW -> OE -> BI | 0.021 | 0.011 | 1.877 | 0.061 | 0.001 | 0.046 | Non-Significant Mediation | 9.33% |
| RW -> TRU -> BI | 0.061 | 0.019 | 3.275 | 0.001 | 0.028 | 0.099 | Significant Mediation | 27.11% |
| TS -> SE -> BI | 0.045 | 0.014 | 3.115 | 0.002 | 0.02 | 0.075 | Significant Mediation | 27.61% |
| TS -> OE -> BI | 0.01 | 0.007 | 1.357 | 0.175 | 0 | 0.027 | Non-Significant Mediation | 6.13% |
| TS -> TRU -> BI | 0.022 | 0.011 | 1.921 | 0.055 | 0.003 | 0.048 | Non-Significant Mediation | 13.5% |
| FC -> SE -> BI | 0.044 | 0.014 | 3.142 | 0.002 | 0.02 | 0.075 | Significant Mediation | 22.45% |
| FC -> OE -> BI | 0.007 | 0.006 | 1.241 | 0.215 | −0.001 | 0.02 | Non-Significant Mediation | 3.57% |
| FC -> TRU -> BI | 0.051 | 0.016 | 3.158 | 0.002 | 0.023 | 0.087 | Significant Mediation | 26.02% |

In addition, the indirect effect of teacher support (TS) on BI through SE reached 27.61%, indicating that the guidance and support of teachers played a positive mediating role in enhancing learners' self-confidence and willingness to use the platform. On the other hand, the mediating effect of facilitating conditions (FC) on BI through SE and TRU was 22.45% and 26.02%, respectively, indicating that the convenience of technology and resources can significantly improve learners' self-efficacy and trust, thereby indirectly improving their intention to use the platform. However, the mediating effects of other paths such as SIE -> OE -> BI, RW -> OE -> BI, and TS -> OE -> BI did not reach a significant level, indicating that the mediating role of outcome expectations (OE) in these paths was relatively weak. These findings overall highlight the core role of self-efficacy and trust as important mediating variables and provide empirical evidence to support the optimal design of educational platforms.

### 5.4. Research Models

Figure 3 presents the results of the 19 path coefficients and their significance levels. Behavioral intention in using the educational metaverse was significantly influenced by factors like rewards, teacher support, facilitating conditions, self-efficacy, outcome expectations, and trust, supporting 17 paths. However, the direct effect of social influence on behavioral intention and the effect of facilitating conditions on outcome expectations were not significant. Thus H1 and H8b were not supported.

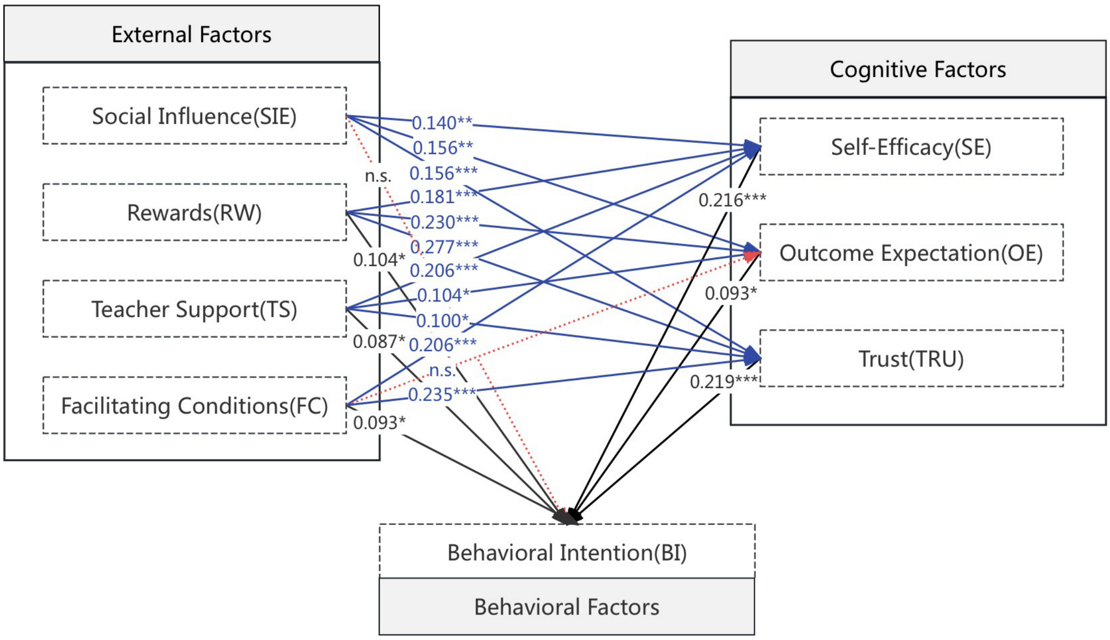


**Figure 3.** Results of research model (*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; n.s. = not significant).

## 6. Discussion

Based on social cognitive theory (SCT), this study explored the key factors which affect design learners' use of a human-AI collaboration platform (EMH-AIc) in the educational metaverse. By constructing a triadic reciprocity framework, the three dimensions of the external environment, cognitive factors, and behavioral intention were integrated to reveal the mechanism which affects the formation of behavioral intention. The model contains eight variables: social influence (SIE), rewards (RW), teacher support (TS), facilitating conditions (FC), self-efficacy (SE), outcome expectations (OE), trust (TRU), and behavioral intention (BI). Although two hypotheses were not supported (i.e., H1 and H8b), the overall research results provide theoretical and empirical support for understanding how design learners form platform usage intentions through external environment and personal cognitive factors and have guiding significance for practical applications.

First, the results reveal the practical implications of external factors on behavioral intention. Social influence did not directly or significantly affect behavioral intention, which suggests that in actual educational environments, design learners' willingness to use the platform depends more on intrinsic motivation and personalized needs rather than social pressure. This conclusion is consistent with the research results of Dahri and Arain et al. [126,127] but different from the conclusions of Altameemi and Wiangkham et al. on social influence [117,128]. This suggests that when promoting new technologies, educational institutions should pay more attention to stimulating learners' interests and intrinsic motivation rather than relying solely on peer or external pressure to promote use. However, social influence indirectly had a significant effect on behavioral intention by enhancing cognitive factors such as self-efficacy and trust, indicating that in a positive learning atmosphere and supportive social environment, social influence can still increase learners' confidence and trust in the platform, thereby increasing their willingness to use the platform. Therefore, educational institutions can indirectly promote platform use by building a supportive social environment to enhance design learners' intrinsic motivation. This respect and support for learners' individual needs can help reduce educational gaps, especially among learners with fewer resources. Virtual platforms can provide a more equal learning experience, thereby improving educational equity.

Secondly, the positive effect of rewards on behavioral intention further supports the research of Bai and Xiao et al. [129,130], indicating that appropriate reward mechanisms can effectively motivate learners to use the platform. Through points, scholarships, or recognition certificates, educational institutions can effectively stimulate students' motivation to participate. Similarly, the positive effect of teacher support on behavioral intention verifies the research conclusions of Fryer and Domen et al. [106,108], highlighting the key role of teachers in technology promotion. Educational institutions can enhance students' willingness to use the platform by training and guiding teachers to ensure that teachers actively promote and demonstrate the use of AI collaboration platforms in the classroom. The positive effect of convenience conditions on behavioral intention supports the findings of Teng et al. [57], indicating that the platform's technology and resource usability are crucial in improving the willingness to use the platform. Therefore, platform designers should continue to optimize the user experience to meet learners' technical needs and enhance their willingness to use it. In particular, for students who lack convenient resources, the convenience of the educational metaverse platform can significantly narrow the gap between them and resource-rich students, thereby providing an effective way to achieve educational equity.

Thirdly, this study confirms the key influence of cognitive factors on behavioral intention, providing practical guidance for designing learners and educational institutions. For example, the significant effect of self-efficacy on behavioral intention indicates that when learners' confidence in their ability to use technology increases, their willingness to use the platform also increases [131]. Educational institutions can help students build confidence by providing technical training and practice opportunities, especially in the early stages of learning. Similarly, the positive effects of outcome expectations and trust further emphasize the key role of platform reliability and data security in improving platform usage intention [132]. Educational institutions and platform developers can enhance students' trust in the platform by demonstrating the effectiveness of the platform and making clear data privacy commitments.

In addition, the finding that external factors indirectly affect behavioral intention through cognitive factors provides strong support for the promotion strategies of the educational metaverse and AI platforms. First, social influence mediates behavioral intention through self-efficacy and trust, which shows that in the educational metaverse environment, although social support and peer influence do not directly affect learners' intention to use a platform, they can indirectly enhance their willingness to use it by improving their self-efficacy and trust. Based on this, when designing promotion strategies, educational institutions should pay more attention to how to establish a supportive learning community and enable learners to feel the indirect influence of social support when using the platform through trust building and self-efficacy improvement. Second, rewards had a significant direct effect on behavioral intention, but the indirect effect through self-efficacy was relatively weak. This suggests that in reward design, educational institutions or platforms should avoid overreliance on indirect channels (such as only improving self-efficacy) and should more directly motivate user participation. For example, through immediate feedback and clear reward mechanisms, learners can directly obtain positive incentives during use, thereby effectively mobilizing their learning enthusiasm. Third, the mediating effect of teacher support on behavioral intention was particularly reflected in the self-efficacy path. This further highlights the important role of teachers in technology promotion. Educational institutions can provide targeted training for teachers so that they can effectively support students in the use of the platform and help students overcome technical barriers in the process of use, thereby significantly improving learners' self-confidence and willingness to continue using it. Finally, the mediating role of trust is significant in multiple paths. This shows that in the process of platform promotion, the establishment of trust is a key factor which cannot be ignored. Educational institutions and platform designers should attach importance to data privacy and security and build user trust through transparent privacy policies and strict data protection measures.

This study provides important practical value for design learners and educational institutions in terms of technology acceptance and application. As the application of educational metaverse and AI collaborative platforms in future design education becomes increasingly common, the results of this study provide empirical support for how to effectively promote students' willingness to use them. By enhancing learners' self-efficacy and trust, educational institutions can more effectively improve students' acceptance of emerging technologies. At the same time, the findings of this study emphasize the potential of the educational metaverse in reducing educational resource gaps and improving educational equity. Compared with previous studies, this study further reveals how external factors and cognitive factors directly or indirectly affect behavioral intentions through a more comprehensive multi-level analysis and provides specific practical suggestions and strategic support for the promotion of educational metaverse and AI platforms so as to better achieve the goal of educational equity.

## 7. Implications and Limitations

### *7.1. Implications*

In terms of theoretical contributions, this study offers several key insights. First, this research applied social cognitive theory (SCT) for the first time to analyze design learners' behavioral intentions within the context of educational metaverse and AI collaboration (EMH-AIc) platforms. This approach expands the application of SCT beyond traditional settings, providing a new theoretical framework for examining user behavior in design education and virtual environments. By integrating the three dimensions of the external environment, cognitive factors, and behavioral intention, this study fills a significant theoretical gap regarding design learning in the educational metaverse. Second, the theoretical model developed in the study effectively revealed the mechanisms behind learners' behavioral intentions on these platforms, offering a solid theoretical foundation for future research on sustained user engagement with educational metaverse and AI platforms. Furthermore, this study highlights how external factors (such as rewards and teacher support) and cognitive factors (like self-efficacy and trust) directly and indirectly influence design learners' usage behaviors. This deepens the understanding of how these factors affect decision-making processes. Lastly, the findings provide new empirical support for the broader academic field, particularly regarding the complexities of behavioral intention formation in technology platforms. These contributions help advance the understanding of user behavior in cutting-edge educational technologies.

From a practical standpoint, this study offers valuable insights for educational metaverse platform developers and administrators. First, this research highlights that enhancing the reward system and teacher support significantly boosts user engagement. Thus, developers should focus on designing more incentive mechanisms, such as real-time feedback on learning outcomes or structured reward systems, to motivate learners' sustained usage. Second, self-efficacy and trust have been identified as critical factors driving platform use. Strengthening users' confidence in their ability to use the platform while ensuring security and data privacy will enhance the platform's attractiveness and user retention. Lastly, this study emphasizes the importance of optimizing technical resources and user experience by providing seamless technical support to ensure the platform's long-term development and user retention. These recommendations offer clear directions for improving educational metaverse platforms and contributing to fostering continuous innovation in the educational technology sector.

### *7.2. Limitations and Future Research Directions*

While this study provides theoretical support for understanding the behavioral intentions of design learners to use the educational metaverse and AI collaboration platform, it also has some limitations. First, the sample size of this study was relatively limited, mainly focusing on design learners in a specific geographical area. This limited sample may limit the extrapolation and generalizability of the results and make it difficult to fully represent learners from different cultural backgrounds or geographical areas. This limitation may limit the applicability of the research results globally, especially for regions with other educational systems or design traditions. Second, this study used cross-sectional data analysis, which made it difficult to capture the dynamic changes in learners' behavioral intentions over time and therefore insufficient to fully explain the motivations and behaviors of design learners when using the platform for a long time. In addition, although the PLS-SEM analysis method effectively revealed the relationship between variables, its causal inference ability was weak and failed to deeply explore the causal mechanism between external factors and behavioral intentions. At the same time, this study did not fully evaluate the practical application utility of complex technologies (such as virtual reality and augmented reality) in the educational metaverse, and thus the discussion on the role of these technologies in improving learning experiences and outcomes was relatively limited.

Based on the above limitations, future research should be improved in many aspects. First, the research should expand the sample size and increase geographical and cultural diversity to enhance the general applicability of the research results. Including design learners from different regions and educational backgrounds in the study can better verify the universality of the research conclusions. Secondly, it is recommended to adopt a longitudinal research design to continuously track learners' behaviors and feedback on the educational metaverse platform, as well as deeply explore the temporal changes and driving factors of behavioral intentions. In addition, future research can consider using experimental designs or causal inference methods to more accurately clarify the causal relationship between external factors, cognitive factors, and behavioral intentions. Finally, it is recommended that future research further explore the application value of technologies such as virtual reality and augmented reality in the educational metaverse and evaluate the actual improvement effects of these technologies on learning experience and learning outcomes. These improvements will provide more solid theoretical and empirical support for the sustainable development and innovative application of the educational metaverse platform.

## 8. Conclusions

This study, through the measurement and validation of a multidimensional model, addressed three core research questions and identified the key factors influencing design learners' use of the educational metaverse for human-AI collaboration (EMH-AIc). Specifically, this research highlights the significance of external factors like rewards and facilitating conditions in driving learners' behavioral intentions, while revealing a limited role for social influence. This finding suggests that educational policy should emphasize the development of platforms which cater to learners' intrinsic motivation and personalized needs rather than relying primarily on peer pressure or social expectations. Teacher support emerged as an essential driver, underscoring the need for educational institutions to equip teachers with tools and training to facilitate effective platform integration. These insights provide not only a theoretical basis for understanding design learners' intentions but also practical guidance for platform design, management, and training frameworks in educational settings.

Moreover, this study confirms the central role of cognitive factors such as self-efficacy, outcome expectations, and trust in shaping behavioral intentions. In particular, self-efficacy and trust acted as critical mediators through which external factors indirectly influenced behavioral intentions. This finding suggests that educational policymakers and platform designers should prioritize initiatives which build learner confidence and establish trust in virtual environments, as these aspects are pivotal to fostering sustained positive engagement. For instance, enhancing data security measures and transparently communicating privacy policies can improve trust, while providing accessible training can boost self-efficacy. These strategies are instrumental in ensuring that learners' initial interest in EMH-AIc platforms translates into long-term, active use.

In addition to informing educational practices within design education, this study opens avenues for exploring EMH-AIc applications in broader educational contexts. Future research should consider adapting and extending this model to other disciplines, particularly those that involve collaborative or project-based learning, such as engineering, business, and the arts. Longitudinal studies could also shed light on how learners' behavioral intentions and interaction patterns evolve over time, thereby providing insights for iterative improvement of the educational metaverse. Furthermore, experimental designs which assess the causal impact of specific features—such as real-time feedback and personalized AI guidance—on learning outcomes could enhance our understanding of EMH-AIc's efficacy across diverse educational fields. These directions will contribute to building a more comprehensive framework for human-AI collaboration in education, aligning with the evolving needs of modern learners and supporting the development of inclusive, adaptable, and innovative learning ecosystems.

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**Informed Consent Statement:** Informed consent was obtained from all subjects involved in this study.

**Data Availability Statement:** All data generated or analyzed during this study are included in this article. The raw data are available from the corresponding author upon reasonable request.

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## Appendix A. Research Constructs and Factor Loading

| Variables | Items and Issues | Factor Loads | References |
|---|---|---|---|
| Social influence (SIE) (4 items) | SIE1: People who influence me believe I should use the educational metaverse for AI collaboration in learning. | 0.812 | [83,102,103] |
| | SIE2: The people important to me support my use of the educational metaverse for AI collaboration in learning. | 0.809 | |
| | SIE3: I plan to use the educational metaverse for AI collaboration because others are using it. | 0.819 | |
| | SIE4: I want to know if my performance in the educational metaverse will leave a good impression on my family, teachers, or friends. | 0.816 | |
| Rewards (RW) (4 items) | RW1: Receiving rewards in the educational metaverse makes me feel recognized for my hard work. | 0.83 | [80,104,105] |
| | RW2: I believe my efforts in the educational metaverse will be rewarded. | 0.832 | |
| | RW3: I might receive extra points, badges, or verbal recognition for using the educational metaverse. | 0.837 | |
| | RW4: I enjoy the reward system in the educational metaverse, and I think it is suitable for the platform. | 0.83 | |

| | | | |
|---|---|---|---|
| Teacher support (TS) (3 items) | TS1: My teacher has provided me with many options on how to complete the assignments. | 0.856 | [106–109] |
| | TS2: From the beginning, my teacher has actively sparked our curiosity and interest in using the educational metaverse for AI collaboration. | 0.88 | |
| | TS3: My teacher has clearly explained the importance of using the educational metaverse for AI collaboration in learning. | 0.838 | |
| Facilitating conditions (FC) (4 items) | FC1: I have the resources necessary to use the educational metaverse. | 0.845 | [83,97,110] |
| | FC2: I know how to use the educational metaverse for AI collaboration in learning. | 0.788 | |
| | FC3: When I face difficulties in the educational metaverse, designated individuals or groups are available to help. | 0.826 | |
| | FC4: I have easy access to the materials I need to develop educational activities through mobile devices. | 0.832 | |
| Self-efficacy (SE) (5 items) | SE1: If I want to, I can easily learn through AI collaboration in the educational metaverse. | 0.838 | [63,75,86,103,111] |
| | SE2: I am confident in my understanding of the functions and content of the educational metaverse for AI collaboration. | 0.795 | |
| | SE3: Even if no one shows me how to use the educational metaverse for AI collaboration, I am confident I can use it. | 0.802 | |
| | SE4: If I want to study through the educational metaverse, it is definitely feasible for me. | 0.814 | |
| | SE5: Whether or not I use the educational metaverse for learning depends mostly on myself. | 0.823 | |
| Outcome expectation (OE) (4 items) | OE1: If I use the educational metaverse for AI collaboration, my learning efficiency will improve. | 0.856 | [86,100,103,111] |
| | OE2: Using the educational metaverse for AI collaboration will increase the quality of my output. | 0.834 | |
| | OE3: Important people in my life (such as family, teachers, or friends) would support me in using the educational metaverse for AI collaboration to improve my learning outcomes. | 0.847 | |
| | OE4: Using the educational metaverse for AI collaboration is useful for my learning. | 0.825 | |
| Trust (TRU) (4 items) | TRU1: The educational metaverse provides reliable resources for design education. | 0.798 | [63,112] |
| | TRU2: The educational information obtained through AI collaboration in the educational metaverse is safe and effective. | 0.844 | |
| | TRU3: The people I interact with on the educational metaverse platform are trustworthy. | 0.84 | |
| | TRU4: Learning on this platform is safe and trustworthy. | 0.843 | |
| Behavioral intention (BI) (4 items) | BI1: I intend to use the educational metaverse for AI collaboration in my studies. | 0.808 | [63,83,102,103,110] |
| | BI2: I expect to continue using the educational metaverse for AI collaboration in learning. | 0.847 | |
| | BI3: I plan to regularly use the educational metaverse for AI collaboration in both learning and work in the future. | 0.833 | |
| | BI4: I think using the educational metaverse for AI collaboration is necessary to meet my learning needs. | 0.829 | |

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