Journal of Information Technology Education: Research

An Official Publication of the Informing Science Institute
InformingScience.org

JITEResearch.org

Volume 25, 2026

APPLYING AND TESTING AN EXTENSIVELY MODIFIED UTAUT-2 MODEL TO EXAMINE PRE-SERVICE TEACHERS' INTENTION TO USE IMMERSIVE VIRTUAL REALITY IN THEIR TEACHING

Emmanuel Fokides*	University of the Aegean, Rhodes, Greece	fokides@aegean.gr
Maria Daskalou	University of the Aegean, Rhodes, Greece	pre23806@rhodes.aegean.gr

* Corresponding author

ABSTRACT

Aim/Purpose	The successful integration of immersive virtual reality (imVR) in education depends on various factors, including educators' views and intentions. Pre-service teachers represent an important demographic as they can play a pivotal role in shaping future educational practices. Therefore, understanding the factors that shape their intentions to use this technology is important.
Background	The Unified Theory of Acceptance and Use of Technology 2 (UTAUT-2) model is widely used in educational technology research to examine behavioral intentions across various groups regarding technology use. However, the model is not without its limitations. One of the most significant shortcomings is that it considers its constructs as exogenous factors influencing behavioral intention, without delving into their interrelationships. To address this limitation, the present study proposed and examined an extensively modified version of the UTAUT-2 model. Additionally, self-efficacy is incorporated as an important factor in this framework.
Methodology	A total of 202 senior students studying at a Department of Education participated in the study, enrolled in a course designed to familiarize them with the design and use of educational imVR applications. Data were collected at the end of the semester, using a questionnaire designed to examine the factors included in the modified UTAUT-2 model.

Accepting Editor Benson Soong │ Received: November 9, 2025 │ Revised: March 15, 2026 │ Accepted: March 25, 2026.

Cite as: Fokides, E., & Daskalou, M. (2026). Applying and testing an extensively modified UTAUT-2 model to examine pre-service teachers' intention to use immersive virtual reality in their teaching. *Journal of Information Technology Education: Research, 25,* Article 11. https://doi.org/10.28945/5752

Contribution	By demonstrating strong in-sample and out-of-sample predictive power, the proposed model offers a strong theoretical and practical framework for understanding pre-service teachers' intentions to use imVR and for promoting imVR adoption in teacher preparation contexts.
Findings	Hedonic motivation, habit, and performance expectancy impacted behavioral intention. Self-efficacy emerged as a central determinant, shaping participants' perceptions of effort expectancy, performance expectancy, and hedonic motivation. Facilitating conditions significantly enhanced self-efficacy, effort expectancy, and habit. Age, sex, and prior experience showed limited or no impact. The structural model demonstrated strong in- and out-of-sample predictive/explanatory power, while the Importance-Performance Map Analysis identified habit and hedonic motivation as key areas requiring improvement.
Recommendations for Practitioners	Education stakeholders should focus on building pre-service teachers' confidence and competence in using imVR through structured, hands-on training and consistent access to well-supported technological environments. Efforts should prioritize cultivating habitual use of imVR by embedding it into regular teaching activities, lesson planning, and semester-long coursework, supported by readily available technical assistance. Finally, enhancing the enjoyment and engagement of imVR experiences can boost teachers' intrinsic motivation, further strengthening their intention to integrate this technology into their future instructional practices.
Recommendations for Researchers	The study illustrates the need to integrate constructs such as self-efficacy, which are not fully addressed in traditional behavioral intention frameworks. Experimental designs that pay attention to sample selection are strongly advised to avoid random or invalid responses when evaluating users' perceptions and intentions related to advanced or emerging technologies. Finally, the study demonstrates the necessity of suggesting and examining models that capture the complex and multifaceted dynamics of imVR adoption.
Future Research	Researchers should further validate the modified UTAUT-2 across diverse educational contexts and participant demographics. Longitudinal and mixed-methods designs are also advised. Expanding the model to include additional contextual variables can provide a more comprehensive understanding of barriers and facilitators influencing teachers' intention to adopt imVR.

Keywords	behavioral intention, immersive virtual reality, pre-service teachers, self-efficacy, UTAUT-2

INTRODUCTION

Virtual reality (VR) is typically defined as a computer-generated simulation designed to represent interactive 3D environments, which may either replicate real-world spaces or construct fictional ones, with the primary objective of fostering a sense of immersion. A more advanced iteration of VR, immersive virtual reality (imVR), intensifies the depth of the immersive experience (Fokides, 2023). This is accomplished through the use of head-mounted displays (HMDs), which detach users from their physical surroundings while providing stereoscopic vision, spatial audio, and real-time motion tracking. Furthermore, recent advancements in the field allow for user interaction just with their hands (there is no longer a need for specialized controllers), enabling a more "natural" form of engagement in the virtual environment.

In the field of education, imVR has emerged as a critical innovation, signaling a shift in pedagogical practice. Rather than maintaining a dependence on traditional methods grounded in analog materials or conventional digital media, this shift introduces a pedagogical framework oriented toward experiential engagement, increased interactivity, and improved instructional effectiveness (Fokides, 2023). In turn, the prospect of integrating imVR into educational settings has sparked considerable debates among researchers, educators, and policymakers. In fact, research indicated that the adoption of imVR has received positive responses from both students and educators, and there is a favorable perception of its implementation in the classroom (e.g., Fokides, 2023; Khukalenko et al., 2022).

At a practical level, imVR is increasingly used to create authentic, risk-free learning experiences across disciplines. For example, in health and medical education, it enables interactive anatomy exploration and procedural practice, allowing learners to visualize complex structures and rehearse skills without patient risk (Pottle, 2019). In engineering and the sciences, students can manipulate virtual apparatus, conduct hazardous or costly experiments safely, and experience phenomena at otherwise inaccessible scales (Radianti et al., 2020). Social sciences and humanities have leveraged imVR for virtual field trips and experiential case studies that situate learners in historical or sociocultural contexts, affording embodied interaction and heightened presence that can deepen understanding and engagement (Antonopoulos et al., 2025).

Several studies and meta-analyses report higher academic achievement and better retention after imVR lessons compared with conventional or 2D instruction (e.g., Antonopoulos et al., 2025; R. Liu et al., 2022; Zhao et al., 2020). Immersive lessons consistently raise enjoyment, presence, interest, and intrinsic motivation, and increase multi-dimensional engagement (cognitive, behavioral, emotional, and social) in K-12 and higher education contexts (e.g., R. Liu et al., 2022; Makransky & Mayer, 2022; Rupp et al., 2019). Emotional responses tend toward positive arousal, greater interest, and satisfaction in laboratory and field implementations (R. Liu et al., 2022).

However, barriers such as cost, hardware logistics, organizational issues, teachers' competencies, and the need for training, complicate adoption (Fokides & Antonopoulos, 2024; Fransson et al., 2020). Teachers' willingness to use imVR also plays a decisive role, as their beliefs and attitudes shape their intentions, which, in turn, shape their pedagogical practices (Tondeur, 2020). Pre-service teachers represent a crucial demographic concerning technology adoption, as their knowledge, skills, and perspectives are likely to have a lasting impact and potential to instigate change. Significant differences in technological adoption intentions may exist between various cohorts and across different technologies (Scherer et al., 2019), highlighting the importance of specifically examining pre-service teachers' behavioral intentions to use imVR in their instruction and the underlying motivations for these intentions. Consequently, in this study, we considered it important to focus on this group.

Behavioral intention models such as the Technology Acceptance Model (TAM) (Davis et al., 1992) and the Unified Theory of Acceptance and Use of Technology-2 (UTAUT-2) (Venkatesh et al., 2012) have been widely applied in technology acceptance research. On the other hand, their use in exploring (pre- or in-service) teachers' intentions to adopt imVR remains limited. Not only that, but the relevant studies often suffered from methodological shortcomings, such as unclear identification of the VR technology used, lack of prior experience, reliance on minimal interventions, absence of systematic training opportunities, and limited reporting on participants' prior exposure (e.g., Boel et al., 2023; Jang et al., 2021; Ko & Shin, 2023). These shortcomings highlight a major gap in understanding how teachers approach imVR integration and point to the need for more rigorous research in this field.

There is also another issue related specifically to UTAUT-2. The model treats its constructs as independent factors and does not fully capture the complex interrelations or indirect effects between them, which are often evident in practice. Moreover, it does not consider the effects of self-efficacy, a central factor in shaping user intentions and behaviors (Bandura, 1977). Therefore, the inclusion of factor interactions and the addition of self-efficacy emerge as a critical need. In fact, we proposed and tested such a model, with rather interesting results (Fokides & Giagiakou, 2025).

Thus, in this study, we have set a two-fold purpose: (i) to examine the validity of our revised model, further tailored to the educational use of imVR, and (ii) to examine the factors (and their interactions) that shape pre-service teachers' intentions to utilize imVR in their future teaching.

Given the above, our study contributes to the advancement of technology acceptance research by extending the UTAUT-2, as we propose a modified model that incorporates self-efficacy as an upstream determinant and explicitly models causal relationships among the UTAUT-2 constructs, drawing on principles from social cognitive theory and prior technology acceptance research. By doing so, our model captures a more nuanced mechanism through which perceptions of imVR shape pre-service teachers' adoption intentions, contributing to a more integrated understanding of cognitive, affective, and contextual determinants of technology use in educational settings.

The remainder of this paper is structured as follows. First, we present the theoretical framework and review the relevant literature that informed our study. Next, we describe the research design, including the proposed model, data collection, and method. This is followed by the presentation and discussion of the results. Finally, we conclude with the implications of our findings for practice, along with the study's limitations and directions for future work.

BACKGROUND

THE UTAUT-2 MODEL

Several models have been developed to predict and explain users' behavioral intentions and actual use of technology. The Technology Acceptance Model (TAM) (Davis et al., 1992) has been one of the most influential ones. Then again, despite its wide application, TAM has faced criticism for being overly simplistic, offering limited ability to predict or explain phenomena, and lacking substantive practical applications (Chuttur, 2009). To overcome these limitations, Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT), synthesizing constructs from several theories, such as the theory of reasoned action (Fishbein & Ajzen, 1975) and the theory of planned behavior (Ajzen, 1991). UTAUT identified four main determinants (performance expectancy, effort expectancy, social influence, and facilitating conditions). Recognizing that UTAUT was originally framed in organizational contexts, Venkatesh et al. (2012) proposed UTAUT-2 to better capture consumer and individual use. UTAUT-2 retains the original constructs while incorporating hedonic motivation, price value, and habit, along with moderating variables such as age, sex, and experience. Though originally developed for consumer contexts, educational technology research has widely adopted UTAUT-2.

In VR and imVR contexts, UTAUT-2 is particularly relevant for two main reasons. First, imVR shares several characteristics with consumer technologies. Their adoption is influenced not only by utilitarian expectations (e.g., improved instructional performance/performance expectancy) but also by experiential and affective factors such as enjoyment, engagement, and novelty. These experiential attributes are particularly salient in VR environments, where immersion and presence contribute strongly to user motivation and continued use. For educators and pre-service teachers, the perceived enjoyment derived from interacting with immersive environments can enhance intrinsic motivation to experiment with and integrate such tools into teaching activities (Fokides & Antonopoulos, 2024). The original UTAUT model does not account for such intrinsic motivational drivers, whereas UTAUT-2 incorporates hedonic motivation and habit, constructs that are highly relevant for technologies characterized by interactive and experiential engagement. Second, educational technology adoption often occurs in contexts that resemble voluntary rather than strictly mandated technology use. Teachers typically decide independently whether and how they will integrate emerging technologies into their instructional practices. In such cases, affective and behavioral mechanisms captured by

UTAUT-2, such as intrinsic enjoyment and habit formation, provide additional explanatory power beyond the organizationally oriented constructs of the original UTAUT model. Moreover, for pre-service teachers still developing their professional practices, the formation of technology-related habits is particularly important, as early experiences with digital tools can shape their long-term instructional preferences. Consequently, examining habit provides insight into whether repeated engagement with imVR during teacher preparation may translate into sustained future use in professional teaching contexts.

In fact, UTAUT-2 has been used to investigate barriers and facilitators of imVR adoption by both educators and students (e.g., Boel et al., 2023; Bower et al., 2020; Y.-Y. Wang & Chuang, 2024; Xie et al., 2024). Moreover, as presented below, studies confirmed that nearly all factors predicting imVR acceptance in educational contexts can be synthesized into UTAUT-2 constructs, particularly behavioral intention and its drivers. Researchers have also extended UTAUT-2 with additional constructs tailored to educational contexts, including Technological Pedagogical Content Knowledge (TPACK), teaching self-efficacy, organizational readiness, training effectiveness, innovation orientation, and technology anxiety (e.g., Kittinger & Law, 2024). Such extensions highlight its flexibility and relevance for analyzing adoption across varied educational settings. In detail, the UTAUT-2 examines the following factors:

- Facilitating conditions describe the extent to which individuals believe that organizational and technical infrastructure exists to support technology use (Venkatesh et al., 2003). In educational contexts, they were found to significantly predict pre- and in-service teachers' behavioral intention to use digital tools (Barakat et al., 2025; Tseng et al., 2022). However, its influence is inconsistent as, in some cases, its effect was weak or non-significant (Kim et al., 2024), especially during later adoption stages when use becomes routine (Marikyan & Papagiannidis, 2022). For VR and imVR, facilitating conditions were also proven crucial (Boel et al., 2023; Bower et al., 2020; C.-Q. Chen et al., 2024; Du & Liang, 2024; Shen et al., 2019; Xie et al., 2024).
- Social influence refers to the extent to which important others suggest to individuals the use of a particular technology (Venkatesh et al., 2003). There is evidence for its effect on technology in education (e.g., J. Liu et al., 2025) and the use of imVR (Boel et al., 2023; Bower et al., 2020; Ogegbo et al., 2024; Shen et al., 2019; Xie et al., 2024). Kittinger and Law's (2024) review confirmed social influence as one of the most consistently examined determinants of technology acceptance in K-12 contexts. Its influence, however, is not universal, as some studies reported no significant effects (e.g., Cimperman et al., 2016), suggesting that its impact depends on contextual and demographic moderators. Social influence also demonstrated complex interactions with other constructs. For example, it mediated the relationship between behavioral intention and technology use (Abdunool et al., 2024) and indirectly affected intention through performance expectancy (Guetz & Bidmon, 2022).
- Effort expectancy refers to the degree of ease of use associated with given technology (Venkatesh et al., 2003). Evidence suggested that it becomes less influential after extended use of technology or when ICT tools are simple enough that effort is negligible (Marikyan & Papagiannidis, 2022). It has also been shown to influence other constructs. For example, it positively affected performance expectancy, since users who find a system easy to use are more likely to view it as beneficial (Camilleri, 2024). In the context of the educational use of VR, Lee and Hwang (2023) showed that hands-on experiences reduced pre-service teachers' perceived effort expectancy. It also seems to have an effect on behavioral intention to use VR and imVR in instruction (Shen et al., 2019; Xie et al., 2024). On the other hand, another study exploring secondary educators' intention to implement imVR found that effort expectancy had no effect (Boel et al., 2023).

- Performance expectancy is defined as the degree to which individuals believe that the use of a system will enhance their job performance (Venkatesh et al., 2003), similar to TAM's concept of perceived usefulness (Davis et al., 1992). It is among the most frequently examined constructs in UTAUT-2 applications in K-12 education (Kittinger & Law, 2024), significantly influencing technology adoption (e.g., Barakat et al., 2025; Du & Liang, 2024; J. Liu et al., 2025). It is influenced by facilitating conditions (Almaiah & Alyoussef, 2019) and social influence (Guetz & Bidmon, 2022). In the context of the educational use of VR and imVR it plays a crucial role in shaping individuals' intentions to adopt these technologies (Boel et al., 2023; Bower et al., 2020; Shen et al., 2019; Sumardani & Lin, 2024; Xie et al., 2024).
- Hedonic motivation refers to the pleasure derived from technology usage, in contrast to the utilitarian dimension of performance expectancy (Venkatesh et al., 2012). Numerous studies underscored its role as a significant determinant of behavioral intention across diverse contexts, including education (e.g., Narayan & Naidu, 2024; Nikolopoulou et al., 2021). Its relevance for educators has been supported by empirical findings (e.g., Barakat et al., 2025; Lee & Hwang, 2023; J. Liu et al., 2025). The pleasure derived from VR and imVR experiences has also been identified as a critical attraction factor (Boel et al., 2023; Bower et al., 2020; Sumardani & Lin, 2024; Xie et al., 2024). In fact, Du and Liang (2024) supported that hedonic motivation (together with social influence, facilitating conditions, effort expectancy, and performance expectancy) is crucial for the sustained use of VR in education.
- Habit refers to the extent to which technology-related behaviors are performed automatically due to past experience. It has been identified as a strong predictor of both behavioral intention and actual technology use. For example, J. Liu et al. (2025) found that habit significantly influenced teachers' use of digital resources, while Barakat et al. (2025) showed that habit predicted continued use of social networking sites for teaching. This means that habit and continuance intention interact; as individuals form habits around technology use, their intentions become more consistent (Söllner et al., 2024). Facilitating conditions play a role in the formation of habits; this is particularly important for educators, who are often left without technical support and training (Alotaibi, 2023).
- The concept of price value refers to individuals' perceived balance between the advantages derived from utilizing a specific technology and the financial cost associated with it (Venkatesh et al., 2012).
- Behavioral intention is a key determinant of whether an individual is likely to engage in a particular action under specific circumstances (Venkatesh et al., 2012). It often provides insights into the degree to which users are open to adopting a new technology.
- Variables such as age, sex, and experience have been utilized as moderating variables in UTAUT-2. Older adults are more sensitive to factors such as facilitating conditions (Venkatesh et al., 2012) and social influence (Chang et al., 2019). Pre-service teachers, who are younger than their in-service counterparts, were found to be more influenced by social pressures, whereas in-service teachers reported that effort expectancy negatively affected their intention to use AR (Ning et al., 2019). Sex also moderates several adoption constructs such as performance expectancy, social influence (Chang et al., 2019), and hedonic motivation (Venkatesh et al., 2012). Prior experience has been linked to stronger behavioral intentions and has moderated the influence of constructs such as social influence and habit (Barakat et al., 2025; Chang et al., 2019). However, the literature also includes studies that question the significance of age, sex, and experience (e.g., Boel et al., 2023; Du & Liang, 2024; E. Y. Wang, Qian, et al., 2024).

Studies Related to the Use of Behavioral Intention Models for Examining Teachers' Intention to Use Immersive Virtual Reality (and Their Limitations)

The body of literature that employed behavioral intention models to examine the intentions of various groups to utilize imVR is sparse. Not only that, but a quick search on Google Scholar and Scopus revealed that research focusing specifically on the intentions of pre- or in-service teachers to incorporate this technology into their pedagogical practices is even more limited and subject to several limitations. For instance, Shen et al. (2019) presented just a video demonstrating the use of HMDs for learning in university students prior to assessing (using UTAUT) their intention to use these devices. Their findings indicated that performance expectancy, effort expectancy, social influence, and facilitating conditions exerted significant positive effects. In another study, the authors applied an extended TAM to assess educators' acceptance of augmented reality (AR) and VR technologies for instruction, although the specific VR technology was not identified, and participants completed only a questionnaire (Ko & Shin, 2023). Despite this, it was determined that self-efficacy and motivational support influenced perceived ease of use.

Similarly, in the research conducted by Ogegbo et al. (2024), the specific VR technology employed, as well as the participants' prior experience, remained ambiguous. The results indicated that pre-service teachers exhibited a high degree of acceptance and intent to use VR, driven by social influence and technology self-efficacy. In the study conducted by Xie et al. (2024), pre-service teachers used a desktop VR training system, and a modified UTAUT-2 model was utilized to assess their behavioral intention to adopt this technology. Although the authors claimed that the participants had used the system and had enough experience, no further details were provided (e.g., duration, modes of use). The findings revealed that their intention was positively influenced by self-efficacy, effort expectancy, social influence, performance expectancy, facilitating conditions, and hedonic motivation.

Further focusing on pre-service teachers, Sumardani and Lin (2024) examined imVR, albeit with only a single intervention. Regardless, the outcomes derived from the TAM model indicated that perceived usefulness and perceived enjoyment affected behavioral intention. Bower et al. (2020), on the other hand, utilized UTAUT-2 to evaluate the intention of pre-service teachers to use imVR following a one-hour lecture accompanied by a two-hour tutorial. Their findings indicated that all the model's constructs had an impact on participants' intentions.

In the study conducted by Boel et al. (2023), the vast majority of the participating educators had no prior experience with imVR, did not receive any training, and were only shown a brief video highlighting the capabilities of this technology. Their analysis of results from an extended UTAUT-2 model revealed that significant predictors of intention included performance expectancy, social influence, facilitating conditions, and hedonic motivation. Facilitating conditions exhibited no effect, and age, sex, and experience lacked any moderating effects. Although Du and Liang (2024) indicated that their study participants (primary and secondary teachers) were selected from schools where VR is employed in teaching, they did not provide specific data regarding their actual experience. Nevertheless, the UTAUT-2 model results indicated that hedonic motivation, performance expectancy, social influence, facilitating conditions, and effort expectancy significantly influenced continued usage intention, whereas habit use did not enhance this intention.

C.-Q. Chen et al. (2024) assessed pre-service teachers who experienced an imVR environment before completing a questionnaire regarding factors related to an extended TAM model. The results indicated that subjective norms significantly influenced their intention to use imVR. Furthermore, attitude and perceived usefulness significantly affected intention, while perceived usefulness and perceived ease of use significantly affected attitude, and perceived ease of use influenced perceived usefulness. Additionally, facilitating conditions had a significant impact on both perceived ease of use and intention.

Lack of evidence regarding teachers' prior experience with AR and VR, as well as the absence of intervention(s), was also the case in Jang et al.'s (2021) study, which used an extended TAM. Their findings suggested that attitude impacted intention, while perceived usefulness and perceived ease of use affected attitude. Further, perceived ease of use and perceived usefulness influenced intention through attitude; motivational support affected attitude through perceived ease of use; and subjective norms influenced attitude through perceived usefulness.

Taken together, the reviewed studies suggest a broadly consistent pattern regarding teachers' intentions to adopt immersive virtual reality. Across both TAM-based and UTAUT-based models, performance expectancy (or perceived usefulness), effort expectancy (or perceived ease of use), hedonic motivation, social influence, and facilitating conditions frequently emerged as significant predictors of intention to use imVR-related technologies in educational contexts. In several cases, self-efficacy has also been identified as an important determinant shaping educators' perceptions of these factors and their intention to adopt VR-based tools. However, despite these converging findings, the existing literature exhibits several common limitations. Many studies relied on minimal or indirect exposure to imVR, such as short demonstrations or videos rather than sustained hands-on use, while others provided limited information regarding the type of VR technology employed or participants' prior experience. Additionally, interventions were often brief or poorly documented, making it difficult to determine whether participants formed their perceptions based on authentic usage experiences. As a result, although prior research provides useful preliminary insights into the determinants of teachers' imVR adoption, it offers only a partial understanding of how these factors operate in realistic educational contexts, highlighting the need for more rigorous experimental designs and theoretically refined models.

THE ROLE OF SELF-EFFICACY

Bandura (1977), who originally introduced the concept of self-efficacy in his social learning framework, defined it as the beliefs individuals have in their capabilities to organize and execute the courses of action required to produce given goals. There is a clear association between teachers' self-efficacy in the use of ICT tools and both their attitudes toward, and their intention to incorporate them into classroom activities (Peng et al., 2024). This influential relationship remains consistent across a range of digital platforms, such as AI tools (Tekin, 2024). Furthermore, self-efficacy frequently operates as a mediating factor in technology adoption models, mediating relationships such as that between perceived ease of use and intention to use technology (Yang & Lou, 2024). Teachers' digital skills, access to computers, and frequency of technology use have been identified as substantial predictors of self-efficacy in the use of ICTs (Ikhlas & Dela Rosa, 2023; Wu et al., 2020). Likewise, teachers' perceptions of both the ease of use and the usefulness of digital tools were found to predict their self-efficacy levels (Wu et al., 2020). Demographic factors further contribute to these dynamics; younger teachers often report greater self-efficacy in the use of technology (Y. Wang, Pradubwate, et al., 2024). However, some studies show no age-related differences (Wu et al., 2020). Sex effects are similarly inconsistent, with some studies detecting no differences between male and female educators (e.g., Y. Wang, Pradubwate, et al., 2024), whereas others report that male teachers tend to exhibit higher self-efficacy in the use of ICTs (e.g., Wu et al., 2020). These findings indicate that self-efficacy in the use of ICTs is likely shaped more by situational factors and individual experiences than by demographic variables alone.

Moreover, there is very limited research -if any- that examined how self-efficacy in using imVR systems or applications (henceforth referred to as SE imVR) influences teachers' behavioral intentions to adopt this technology. Despite conducting a thorough literature review on this topic, we were able to identify just two relevant studies (Gupta & Bhaskar, 2023; Xie et al., 2024). Although in both cases the authors reported a direct impact of self-efficacy on behavioral intention, we have to note that their studies utilized desktop VR rather than imVR. This knowledge gap calls for further examination as teacher self-efficacy strongly correlates with technology adoption, as we elaborated in the preceding paragraph.

DO WE NEED AN EXTENSIVELY MODIFIED UTAUT-2 MODEL?

Although UTAUT-2 has served as a theoretical basis for a large number of studies across an assortment of contexts, we argue that there is potential for enhancement given its limitations. Probably the most prominent one is the treatment of its constructs. All except behavioral intention and use behavior are treated as exogenous variables, limiting the analysis of their interrelations. Yet, studies have suggested that more complex hierarchical and cascading relationships between these constructs better reflect the process through which individuals evaluate and adopt technologies (Dwivedi et al., 2019; Tamilmani et al., 2021). For example, a link between facilitating conditions and effort expectancy is quite logical. The same applies to the indirect effects (also absent in the original UTAUT-2). TAM, on the other hand, allows for the examination of such paths, though in terms of comprehensiveness, it is more parsimonious compared to UTAUT-2. Considering the above, combining the strengths of both TAM and UTAUT-2 into one model presents itself as an interesting idea. Furthermore, as we detailed in the section The Role of Self-efficacy, this concept is crucial for understanding user intentions and behaviors and relates to almost all constructs in UTAUT-2. As it is not included in UTAUT-2, integrating is essential. In fact, we tested such a model in a previous study (Fokides & Giagiakou, 2025), though in a different context, with intriguing results. As this new model requires further validation, we decided to employ it in this study as well.

We should clarify that the proposed model was developed primarily through a theory-driven process. The selection of constructs was based on the UTAUT-2 framework, while the inclusion of self-efficacy was informed by the social cognitive theory proposed by Bandura (1977). In addition, the specification of directional relationships among constructs was guided by theoretical arguments and empirical findings from technology acceptance research, particularly studies derived from the TAM (Davis et al., 1992). Therefore, we defined the hypothesized paths *a priori*, based on conceptual reasoning and prior empirical evidence, rather than deriving them from exploratory data analysis. We conducted the PLS-SEM analysis, as detailed in a subsequent section, to evaluate these theoretically specified relationships and assess the explanatory and predictive power of the proposed model.

As a result of the above, we categorized the constructs Facilitating Conditions (Fac. cond.) and Social Influence (Soc. inf.) as exogenous variables, affecting all the model's factors. Facilitating conditions relate to users' work environment, over which they typically have minimal control (rendering them exogenous). Similarly, social influence is also an exogenous variable, as it relates to opinions others have on specific issues. Prior research consistently positioned these constructs as antecedents influencing users' beliefs and intentions regarding technology use (Venkatesh et al., 2003, 2012). Moreover, Bandura (1977) implied that self-efficacy is constructed through resources that enable mastery experiences and through the social environment via verbal persuasion and vicarious learning. In line with this reasoning, we assumed that both Fac cond. and Soc. inf. affect all factors, hypothesizing that:

- RH1a-f. Fac. cond. directly and/or indirectly affect: (a) SE imVR, (b) Effort expectancy (Eff. exp.), (c) Performance expectancy (Perf. exp.), (d) hedonic motivation (Hed. mot.), (e) habit (Habit), and (f) behavioral intention (Beh. int.).
- RH2a-f. Soc. inf. directly and/or indirectly affects: (a) SE imVR, (b) Eff. exp., (c) Perf. exp., (d) Hed. mot., (e) Habit, and (f) Beh. int.

We treated self-efficacy, defined in this study as Self-Efficacy in the use of imVR (SE imVR), as a first-order endogenous variable, influenced by the exogenous factors. While research suggests that self-efficacy is influenced by factors such as effort and performance expectancy (Wu et al., 2020), Bandura (1977) argued that self-efficacy influences cognitive functions, motivation levels, persistence, emotional states, and performance outcomes. In technology acceptance research, self-efficacy has frequently been conceptualized as an upstream determinant of core belief constructs such as perceived ease of use and perceived usefulness in models such as TAM (Scherer et al., 2019; Teo, 2009). Accordingly, positioning self-efficacy as an antecedent to effort expectancy reflects a well-established causal relationship in the technology adoption literature. Consequently, we regarded SE imVR as the antecedent of the other constructs present in the modified UTAUT-2 model. Therefore, we hypothesized that:

- RH3a-e. SE imVR directly and/or indirectly affects: (a) Eff. exp., (b) Perf. exp., (c) Hed. mot., (d) Habit, and (e) Beh. int.

We conceptualized effort expectancy (Eff. exp.) as a second-order endogenous construct. External factors (such as Fac. cond. and Soc. inf.) may influence individuals' perceptions of imVR's ease of use, while those confident in their abilities (SE imVR in this case) are more likely to deem it easier to operate. Moreover, there is a well-established relationship between perceived ease of use and perceived usefulness in the TAM framework (Davis et al., 1992). Empirical studies in educational technology adoption have repeatedly confirmed this causal relationship (e.g., Camilleri, 2024). Therefore, it is logical to assume that Eff. exp. influences the remaining constructs in the model. That is because a tool perceived as easy to use is likely to be regarded as more useful and enjoyable, fostering ongoing usage and the intention to continue using it. As a result, we hypothesized that:

- RH4-d. Eff. exp. directly and/or indirectly affects: (a) Perf. exp., (b) Hed. mot., (c) Habit, and (d) Beh. int.

Performance expectancy (Perf. exp.) was modeled as influencing Hed. mot., Habit, and Beh. int. This ordering reflects the assumption that when individuals perceive a technology as beneficial for achieving their goals, they are more likely to experience positive affective responses toward its use and engage with it more frequently. This transition from utilitarian evaluation to affective responses is supported by Cognitive Appraisal Theory (Lazarus, 1991). When a user determines that a technology successfully facilitates their goals (high performance expectancy), this goal-congruent cognitive appraisal generates positive affective states. Therefore, we hypothesized that:

- RH5a-c. Perf. exp. directly and/or indirectly affects: (a) Hed. mot., (b) Habit, and (c) Beh. int.

We treated hedonic motivation (Hed. mot.) as a fourth-order endogenous construct influencing both Habit and Beh. int. The rationale for this positioning is rooted in reinforcement learning and dual-system theory. Experiencing intrinsic pleasure and gratification (hedonic motivation) provides the necessary psychological reward to transition a deliberative behavior into an automatic, habitual routine (Chiu et al., 2014). Therefore, we hypothesized that:

- RH6a-b. Hed. mot. directly and/or indirectly affects: (a) Habit and (b) Beh. int.

In turn, we conceived Habit as a fifth-order endogenous construct that impacts one's intention to use imVR. This reflects the notion that there is an interaction between habit and intention which increases over time (Söllner et al., 2024). As a result, we hypothesized that:

- RH7. Habit directly affects Beh. int.

We treated sex, age, and experience (defined as the experience in using imVR, Exp.) as control variables, affecting all factors, hypothesizing that:

- RH8a-h. Age directly and/or indirectly affects: (a) Fac. cond., (b) Soc. inf., (c) SE imVR, (d) Eff. exp., (e) Perf. exp., (f) Hed. mot., (g) Habit, and (h) Beh. int.
- RH9a-h. Sex directly and/or indirectly affects: (a) Fac. cond., (b) Soc. inf., (c) SE imVR, (d) Eff. exp., (e) Perf. exp., (f) Hed. mot., (g) Habit, and (h) Beh. int.
- RH10a-h. Exp. directly and/or indirectly affects: (a) Fac. cond., (b) Soc. inf., (c) SE imVR, (d) Eff. exp., (e) Perf. exp., (f) Hed. mot., (g) Habit, and (h) Beh. int.

Behavioral intention (Beh. int.) served as our primary dependent variable, affected by all the preceding constructs. Although relevant in certain contexts, we deemed the constructs labeled as Price

Value and Use Behavior unsuitable for this study, and we excluded them. The rationale for excluding the former was primarily rooted in our research objective, which emphasized examining intentions rather than evaluating actual usage patterns. Furthermore, as our sample consisted of students engaged in a course related to imVR (as elaborated in a coming section), we theorized that the use behaviors observed may not accurately reflect the complexities inherent in real-world teaching environments. The exclusion of price value was contingent upon the contextual parameters of our study. Given that our participants were situated in an institutional framework that provided access to imVR resources at no direct cost to them, financial considerations did not bear immediate relevance to their intentions regarding technology adoption.

Moreover, as we wanted to validate our model's predictive power, we hypothesized that:

- RH11. The model will demonstrate sufficient in- and out-of-sample predictive/explanatory power.

In addition, we recognized the significance of exploring strategies to enhance pre-service teachers' intentions to integrate imVR applications into their instructional practices. This consideration led us to formulate the following research question:

- RQ1. Which of the aforementioned factors should be enhanced to further strengthen participants' behavioral intention to use imVR?

We present the conceptual framework for the modified UTAUT-2 model we propose in Figure 1.

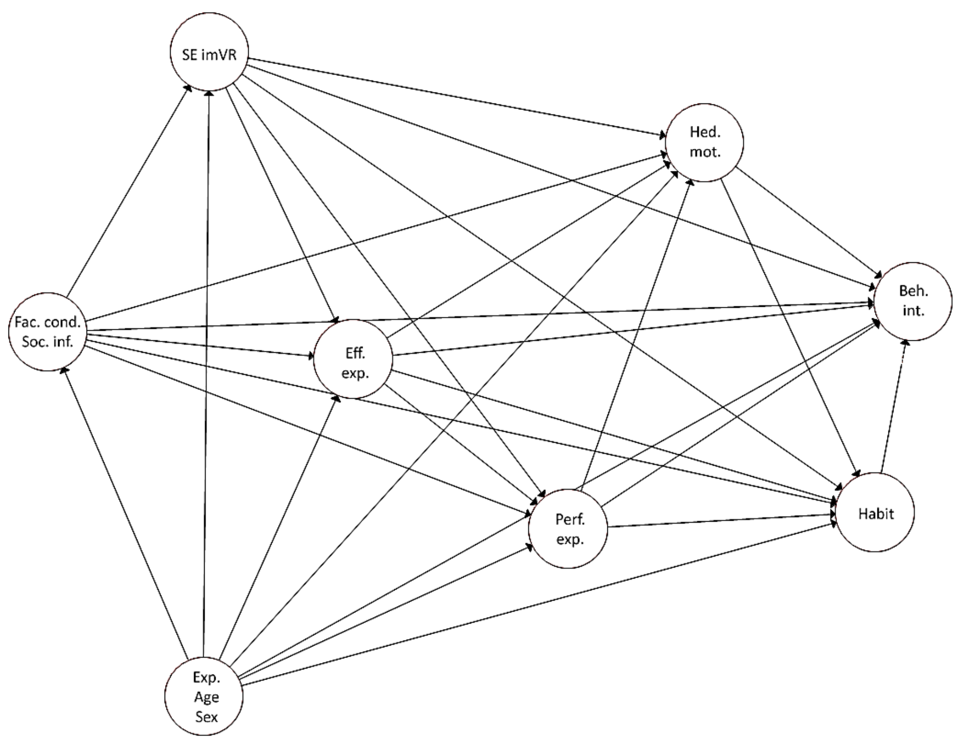


Figure 1. The proposed model

Note. To enhance clarity, certain factors were consolidated, reducing the total number of arrows displayed.

Summarizing the above, we can support that our study extends the UTAUT-2 in two ways. First, it introduces self-efficacy as an upstream determinant, drawing on the social cognitive theory of Bandura (1977) to capture how individuals' beliefs about their capabilities shape subsequent perceptions of effort, performance outcomes, and enjoyment when interacting with a technology. Second, we specify a model with theoretically grounded relationships among UTAUT-2 constructs, moving beyond the common practice of treating them as independent predictors of behavioral intention. By allowing for indirect and hierarchical relationships among contextual, cognitive, and affective factors, our framework conceptualizes technology adoption as a process rather than a set of parallel influences. In doing so, we provide a more integrated account of how pre-service teachers form intentions to adopt imVR in educational contexts, extending the explanatory scope of existing UTAUT-based research.

METHOD

SAMPLE AND PROCEDURE

Establishing an appropriate sample size is fundamental, as it influences the validity and reliability of findings. For this study, we selected Partial Least Squares-Structural Equation Modeling (PLS-SEM) as our method for data analysis, a decision that we will discuss in detail in the Results section. Sample size estimation in PLS-SEM research relies on the "10-times rule." This rule suggests that researchers recruit a sample at least ten times larger than the greatest number of structural paths targeting a single latent variable in the model (Barclay et al., 1995). In our framework, the variable with the highest number of predictors had ten (thus, ten incoming paths); hence, our minimum recommended sample size was 100 participants. To reinforce the accuracy of this estimation, we conducted an *a priori* power analysis using the G*Power software (Faul et al., 2007). By specifying a medium effect size (f^2 = 0.15), a statistical power of 0.95 for minimizing Type II errors (which is well above the standard threshold of 0.80), a significance level of 0.05, and 10 predictors, the analysis produced a minimum sample size requirement of 172 participants.

As we demonstrated in a previous section, it is common in the literature for VR/imVR studies to overlook whether participants possess sufficient knowledge or meaningful perspectives on the topic, which can undermine data quality through uninformed or random responses. Therefore, we had reason to require participants to be familiar with or have formed opinions about this technology. As a result, we specifically invited pre-service teachers (senior students from a Department of Primary Education) who were enrolled in a specialized course. This course not only introduces the theoretical foundations of immersive technology in education but also consistently incorporates hands-on interactions with imVR applications and the use of HMDs. Students are also required to design, develop, and test multiple small-scale imVR educational applications, culminating in the creation of a complex project. As our study took place at the end of the academic term, we were confident that participants had sufficient exposure and opportunity to form well-grounded opinions regarding imVR, rendering them an ideal target group for our research objectives.

In total, 202 students volunteered to participate, significantly exceeding our calculated minimum sample size. Participation was voluntary and open; there were no exclusion criteria applied beyond the requirements outlined above. We provide additional demographic information about the sample in the Results section.

All procedures adhered to ethical standards and received approval from the Research and Ethics Committee of the Department of Primary Education at the University of the Aegean. In compliance with ethical practices, we informed participants about the anonymity and confidentiality of their responses. The act of submitting the online questionnaire (administered through Google Forms and detailed in the Instrument section), served as participants' informed consent to take part in the study.

INSTRUMENT

To address the research hypotheses, we utilized a questionnaire. The development of the questionnaire items was grounded in two sources. First, items were drawn from the influential work of Venkatesh et al. (2012), who introduced the UTAUT-2 framework. This reference provided validated measurement items for Beh. int. (three items), Eff. exp. (four items), Per. Exp. (three items), Fac. cond. (four items), Soc. inf. (three items), Hed. mot. (three items), and Habit (four items). Second, we integrated the New General Self-Efficacy Scale (NGSES) (G. Chen et al., 2001) into the questionnaire. The NGSES comprises eight items designed to assess self-efficacy across a broad spectrum of contexts and professional tasks.

Though the instrument was validated in a previous study (Fokides & Giagiakou, 2025), to further guarantee its validity and methodological rigor, we re-implemented a modified form of the Decision Delphi process (Rauch, 1979). We uploaded the entire pool of questionnaire items, including both the original English texts and their Greek translations to a shared document and we engaged four experts in educational technology to provide recommendations regarding: (i) the suitability of the language utilized for the intended audience, (ii) the inclusion, omission, or re-wording of items, and (iii) whether each set of items accurately reflected the theoretical construct to which they have been allocated. The experts' observations and recommendations were documented again in a collaborative document, facilitating access for other scholars to review and contribute their insights. After multiple iterations of feedback and discourse, a consensus emerged, leading the panel of experts to formulate their final proposal. Following that, we invited twenty pre-service teachers (who were not part of the main study sample) to evaluate item clarity and comprehensibility and to propose further enhancements. Feedback from this group prompted additional rewording and fine-tuning of certain items. As an additional precautionary step, the revised items were resubmitted to the expert panel for final review and approval. The finalized instrument employed a five-point Likert-type scale (see Appendix A). We included three supplementary items in the instrument to collect participants' age, sex, and expertise in the use of imVR applications.

RESULTS

INITIAL DATA PROCESSING

As we previously mentioned, 202 pre-service teachers took part in our research. The majority of the sample consisted of females (n = 150, 74.26%), and the mean age was approximately 21.6 years (M = 21.56, SD = 3.84). We expected this sex disparity, as women constitute the majority of both in-service teachers and students enrolled in Primary Education Departments in Greece. In terms of experience with imVR, the average score was low (M = 2.04, SD = 1.02).

Given that our study had an exploratory orientation, which may contribute to new theoretical insights, we concluded that Partial Least Squares Structural Equation Modeling (PLS-SEM) was the most suitable statistical approach (J. F. Hair et al., 2019). In accordance with recommendations from J. F. Hair et al. (2019), we conducted a series of preliminary assessments before performing the PLS-SEM analysis. First, we examined the dataset for missing data and for participants who did not provide varied responses (i.e., participants with a standard deviation of zero across their answers). No individuals satisfied the criteria for exclusion. We evaluated items' reliability by examining their loadings. Although two items recorded loadings slightly below the optimal threshold of 0.70, both surpassed 0.60 (Fac. cond.4 = 0.61; SE imVR7 = 0.67), indicating acceptable item reliability (Appendix B, Table B1). We used rho_A and Cronbach's alpha to establish the items' internal consistency and reliability. We detected no reliability issues (Appendix B, Table B2). To assess convergent validity, we reviewed the average variance extracted (AVE) for all constructs, all of which exceeded the 0.50 benchmark, confirming convergent validity (Appendix B, Table B2). We examined discriminant validity using the heterotrait-monotrait ratio (HTMT). All values remained below the conservative threshold of 0.85, supporting discriminant validity (Appendix B, Table B3). Finally, we investigated potential multicollinearity through the Variable Inflation Factor (VIF) for each item. While almost all items exhibited VIF values well below the cutoff of 5.0, two items were marginally above the threshold (Habit2 = 5.23; Hed. mot2 = 5.06, Appendix B, Table B4). On the other hand, prior research noted that VIF thresholds in PLS-SEM should be treated as guidelines rather than strict cut-off criteria, as they are not indicators of definite multicollinearity problems (J. F. Hair et al., 2011). In addition, PLS-SEM is generally robust to moderate levels of multicollinearity, especially compared with covariance-based SEM (Henseler et al., 2009). Furthermore, because the indicators belonged to reflective constructs, a certain degree of correlation among items is expected (Chin, 1998). For these reasons and given that the deviation from the recommended threshold was marginal and no other issues were noted, we retained these indicators.

The PLS-SEM Results

The next phase of our analysis consisted of assessing the structural model through the examination of the PLS-SEM results. Please note that we implemented a Bias-Corrected and Accelerated bootstrap technique with 10,000 subsamples to evaluate the statistical significance and magnitude of the path coefficients (J. F. Hair et al., 2019). We present the statistically significant findings in Tables 1 to 3, while in Figure 2 we illustrate the final model. The full set of results can be found in Appendix C.

To enhance clarity, only the statistically significant direct paths are depicted. The coefficients for each path are displayed as numerical values along the arrows, and the figures within the circles denote the factors' R^2 values.

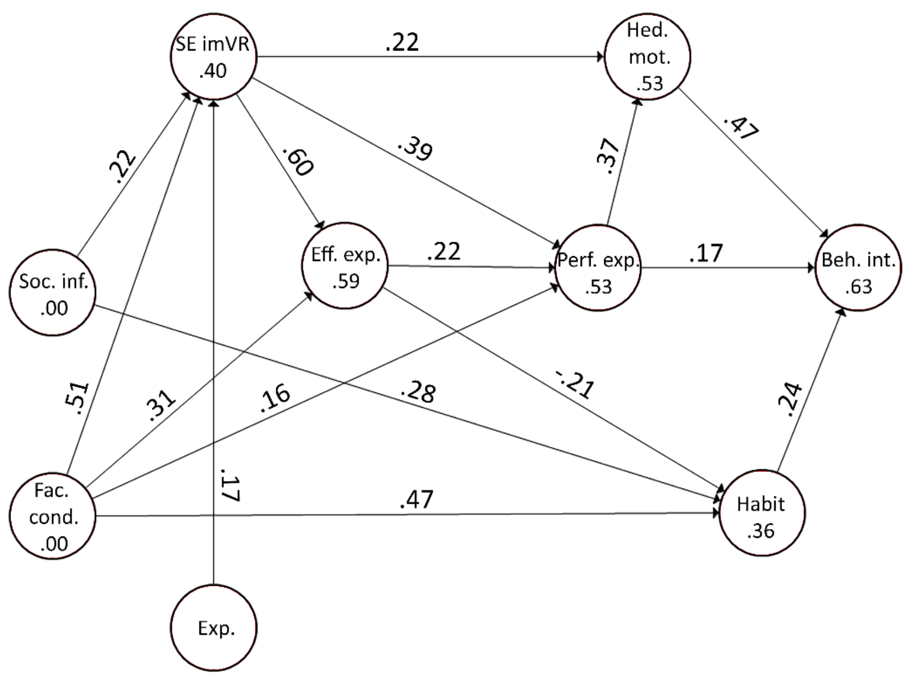


Figure 2. The final model

Table 1. The results of the PLS-SEM, direct effects

Path	*t*	*p*	*β*	f^2	Interpretation
Eff. exp. -> Habit	2.17	0.030	-0.21	0.03	Modest path, small effect
Eff. exp. -> Perf. exp.	2.87	0.004	0.22	0.04	Modest path, small effect
Exp. -> SE imVR	3.25	0.001	0.17	0.05	Modest path, small effect
Fac. cond. -> Eff. exp.	5.22	<0.001	0.31	0.15	Moderate path, medium effect
Fac. cond. -> Habit	5.54	<0.001	0.47	0.18	Moderate path, medium effect
Fac. cond. -> Perf. exp.	2.16	0.031	0.16	0.03	Modest path, small effect
Fac. cond. -> SE imVR	7.29	<0.001	0.51	0.37	Strong path, large effect

Path	t	p	β	f^2	Interpretation
Habit -> Beh. int.	4.48	<0.001	0.24	0.10	Modest path, small effect
Hed. mot. -> Beh. int.	6.51	<0.001	0.47	0.28	Moderate path, medium effect
Perf. exp. -> Beh. int.	2.26	0.024	0.17	0.03	Modest path, small effect
Perf. exp. -> Hed. mot.	4.58	<0.001	0.37	0.14	Moderate path, small effect
SE imVR -> Eff. exp.	9.88	<0.001	0.60	0.53	Strong path, large effect
SE imVR -> Hed. mot.	2.38	0.017	0.22	0.04	Modest path, small effect
SE imVR -> Perf. exp.	4.74	<0.001	0.39	0.13	Moderate path, small effect
Soc. inf. -> Habit	3.59	<0.001	0.28	0.09	Modest path, small effect
Soc. inf. -> SE imVR	3.44	0.001	0.22	0.07	Modest path, small effect

Notes: "-" is used to denote results that are not statistically significant. For interpreting path coefficients, the following criteria are utilized: β values between 0.0 and 0.10 indicate a weak relationship, those from 0.11 to 0.30 reflect a modest relationship; β values ranging from 0.31 to 0.50 signify a moderate relationship, and β values above 0.50 indicate a strong relationship (J. F. Hair & Alamer, 2022). Effect size is evaluated according to these standards: an f^2 value of 0.35 or greater indicates a large effect, f^2 values of 0.15 or higher denote a medium effect, f^2 values of 0.02 or higher suggest a small effect, while f^2 values less than 0.02 are interpreted as negligible (Cohen, 2013).

Table 2. The results of the PLS-SEM, indirect effects

Path	t	p	β	Interpretation
Eff. exp.-> Hed. mot.	2.69	0.007	0.08	Weak path
Fac. cond. -> Beh. int.	6.60	< 0.001	0.41	Moderate path
Fac. cond. -> Eff. exp.	6.43	< 0.001	0.31	Moderate path
Fac. cond. -> Hed. mot.	4.70	< 0.001	0.39	Moderate path
Fac. cond. -> Perf. exp.	5.84	< 0.001	0.34	Moderate path
Perf. exp. -> Beh. int.	4.30	< 0.001	0.19	Modest path
SE imVR -> Beh. int.	5.34	< 0.001	0.36	Moderate path
SE imVR -> Hed. mot.	4.40	< 0.001	0.29	Modest path
SE imVR -> Perf. exp.	2.71	0.007	0.13	Modest path
Soc. inf. -> Beh. int.	3.94	< 0.001	0.19	Modest path
Soc. inf. -> Eff. exp.	3.09	0.002	0.13	Modest path
Soc. inf. -> Hed. mot.	2.60	0.009	0.12	Modest path
Soc. inf. -> Perf. exp.	2.30	0.022	0.09	Weak path

Note. Effect sizes cannot be calculated for indirect effects.

Table 3. The model's in-sample explanatory power/predictive power

Factor	*Adj. R^2*	Interpretation
Beh. int.	0.63	Strong explanation
Eff. exp.	0.59	Strong explanation
Fac. cond.	0.00	Weak explanation
Habit	0.36	Moderate explanation
Hed. mot.	0.53	Strong explanation
Perf. exp.	0.53	Strong explanation

Factor	*Adj. R^2*	Interpretation
SE imVR	0.40	Moderate explanation
Soc. inf.	0.00	Weak explanation

Note. The interpretation of R^2 values is categorized as follows: values between 0.0 and 0.10 signify weak explanatory or predictive power; values from 0.11 to 0.30 represent modest power; those falling between 0.31 and 0.50 indicate a moderate degree; and values exceeding 0.50 are indicative of strong explanatory/predictive capability (J. Hair & Alamer, 2022).

OUT OF SAMPLE PREDICTIVE POWER

The Adj. R^2 value for Beh. int. was 0.63, suggesting a strong in-sample explanatory/predictive power for this factor (J. Hair & Alamer, 2022). However, we have to stress that achieving strong results on the training dataset (in-sample predictive power) does not necessarily indicate that the model will perform in the same manner when applied to new, unseen data. Therefore, we deemed it essential to assess the out-of-sample predictive power of the model to have an indication of the model's generalizability and ability to deliver reliable predictions in practical applications. To this end, we employed the PLSpredict procedure. While several indicators can be used, J. F. Hair et al. (2019) suggested that the more reliable one is the comparison of the root mean squared error (RMSE) values from two sources: predictions generated by the PLS-SEM model and those from a simple linear regression model (LM). The PLS-SEM model yielded lower RMSE values than the naïve LM for the majority of indicators (in 27 out of the 31 cases). On the basis of this result, we can support that the model possesses considerable in- and out-of-sample predictive power.

IMPORTANCE-PERFORMANCE MAP ANALYSIS

In the final phase, we conducted an Importance-Performance Map Analysis (IPMA) to gain insights into the performance of each factor. The IPMA enables the simultaneous assessment of both the importance and performance of the examined factors, facilitating decision-making and the prioritization of actions (J. F. Hair et al., 2023). Given that one of the objectives of our study was to determine how the intention of pre-service teachers to use imVR could be enhanced (see RQ1), the IPMA was employed with this target in mind. The findings revealed that the variables Hed. mot. and Habit (to a large extent) warrant attention (Table 4 and Figure 3).

Table 4. The results of the IPMA analysis

Factor	Importance	Performance
Age	0.03	6.41
Eff. exp.	0.05	63.96
Exp.	0.05	26.73
Fac. cond.	0.12	59.17
Habit	0.24	33.86
Hed. mot.	0.47	75.10
Perf. exp.	0.17	71.19
SE imVR	-0.02	63.09
Sex	-0.03	74.26
Soc. inf	-0.02	52.68

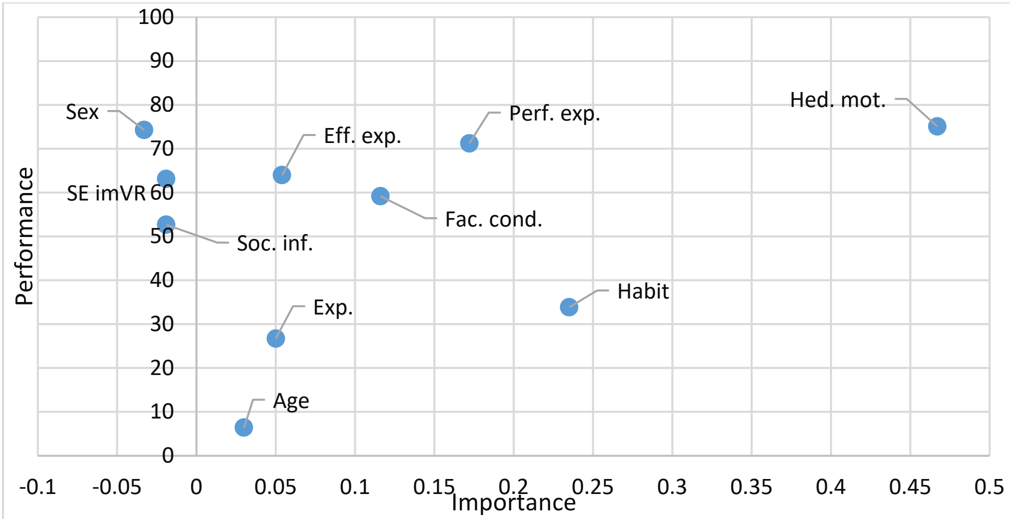


Figure 3. Graphical representation of the IPMA analysis

Summary of the Results, Response to the Research Hypotheses, and Question

Summarizing the findings, the following can be noted in relation to the research hypotheses and question:

- RH1a-f. Fac. cond. had a statistically significant impact on SE imVR, Eff. exp., Perf. exp., and Habit. It had no direct impact on Hed. mot. or Beh. int. Yet, with the exception of Habit, it had indirect effects on all the other factors (Eff. exp., Perf. exp., Hed. mot., and Beh. int.).
- RH2a-f. Soc. inf. had statistically significant direct effects only on SE imVR and Habit. As far as its indirect effects are concerned, it had statistically significant ones on Eff. exp., Perf. exp., Hed. mot., and Beh. int.
- RH3a-e. SE imVR had statistically significant direct effects on Eff. exp., Perf. exp., and Hed. mot., but no direct effects on Habit and Beh. int. In terms of indirect effects, it had statistically significant ones on Perf. exp. (through Eff. exp.), Hed. mot. (through Eff. exp. and Perf. exp.), and on Beh. int.
- RH4a-d. Eff. exp. had statistically significant direct effects on Perf. exp. and Habit, but none on Hed. mot. and Beh. int. The only indirect effect it had was on Hed. mot. (through Perf. exp.)
- RH5a-c. Perf. exp. had a statistically significant impact on Hed. mot. and Beh. int. but not on Habit. It also had an indirect impact on Beh. int. (through Hed. mot.).
- RH6a-b. Hed. mot. had a statistically significant direct effect on Beh. int. but not on Habit. We noted no indirect effects.
- RH7. Habit had a statistically significant impact on Beh. int.
- RH8a-h. Age had no direct or indirect effects on any factor.
- RH9a-h. Sex had no direct or indirect effects on any factor.
- RH10a-h. Exp. directly affected only SE imVR. It had no other direct or indirect effects.
- RH11. The results indicate that the model we proposed exhibits strong in- and out-of-sample predictive/explanatory power, demonstrating its reliability and generalizability.
- RQ1. Regarding factors requiring attention, it is clear that Habit stands out as the most critical one, followed by Hed. mot. (to a far lesser degree).

DISCUSSION

The analysis of the data yielded several intriguing findings. However, we have to stress that the substantial reconfiguration of the UTAUT-2 presents challenges to aligning the current findings with those reported in earlier studies.

DISCUSSION OF THE RESULTS RELATED TO THE IMPACT OF FACILITATING CONDITIONS (RH1A-F) AND SOCIAL INFLUENCE (RH2A-F)

We identified a significant direct impact of Fac. cond. on SE imVR, with a large effect size ($\beta = 0.51$, $p < 0.001$, $f^2 = 0.37$). This result aligns with prior studies demonstrating that facilitating conditions influence self-efficacy (e.g., Menno et al., 2024). Consequently, we can support the notion that structured and supportive frameworks are instrumental in enhancing educators' self-efficacy in utilizing imVR. Furthermore, we found Fac. cond. to directly and indirectly influence Eff. exp. (direct effects: $\beta = 0.31$, $p < 0.001$, $f^2 = 0.15$; indirect effects: $\beta = 0.31$, $p < 0.001$) and Perf. exp. (direct effects: $\beta = 0.16$, $p = 0.031$, $f^2 = 0.03$; indirect effects: $\beta = 0.34$, $p < 0.001$). These findings extend the literature (e.g., C.-Q. Chen et al., 2024) by suggesting that facilitating conditions also shape pre-service teachers' perceptions of imVR's usefulness. The influence of Fac. cond. on Habit (direct effects: $\beta = 0.47$, $p < 0.001$, $f^2 = 0.18$; indirect effects: $\beta = 0.39$, $p < 0.001$) further highlights the importance of providing adequately resourced imVR environments to foster habitual use among pre-service teachers, as others suggested (Alotaibi, 2023).

On the other hand, the non-significant direct effects of Fac. cond. on Hed. mot. and Beh. int. appear to contrast with previous studies in the field of VR and imVR adoption by pre- and in-service teachers (e.g., Boel et al., 2023; Bower et al., 2020; C.-Q. Chen et al., 2024; Du & Liang, 2024; Shen et al., 2019; Xie et al., 2024). One plausible explanation for this discrepancy is that, while infrastructure establishes the foundation for engagement, intrinsic factors like self-efficacy and perceived ease of use may play a more significant role in driving enjoyment and intention. The substantial indirect effect of Fac. cond. on Beh. int. ($\beta = 0.41$, $p < 0.001$), mediated through pathways involving SE imVR and other factors, lends empirical support to that assumption.

Soc. inf. had direct effects on SE imVR ($\beta = 0.22$, $p = 0.001$, $f^2 = 0.07$) and Habit ($\beta = 0.28$, $p < 0.001$, $f^2 = 0.09$). It also had indirect effects on Eff. exp. ($\beta = 0.13$, $p = 0.002$), Perf. exp. ($\beta = 0.09$, $p = 0.022$), Hed. mot. ($\beta = 0.12$, $p = 0.009$), and Beh. int. ($\beta = 0.19$, $p < 0.001$). The significant link between social influence and self-efficacy aligns with the view that external encouragement can build individuals' confidence (Narayanan et al., 2023), including the use of VR (Shen et al., 2019). Similarly, the significant effect of social influence on habit suggests that recommendations from influential figures may create an environment that fosters habitual behaviors. Interestingly, social influence did not exert significant direct effects on effort expectancy, performance expectancy, and hedonic motivation. In our view, this result suggests that while it may catalyze initial interest, it may not suffice to directly influence technical perceptions or intrinsic motivation.

Literature suggested that social influence translates into intention to adopt technology (e.g., Kittinger & Law, 2024; J. Liu et al., 2025), including VR and imVR (Boel et al., 2023; C.-Q. Chen et al., 2024; Ogegbo et al., 2024; Shen et al., 2019; Xie et al., 2024). Yet, our findings challenge this assumption, as we found no such direct effect. It seems that social influence's impact depends on contextual moderators, as others suggested (Cimperman et al., 2016). The fact that we found an indirect effect of social influence on intention (through SE imVR and Habit), supports our hypothesis.

DISCUSSION OF THE RESULTS RELATED TO THE IMPACT OF SELF-EFFICACY (RH3A-E)

The limited literature related to the role of self-efficacy in imVR (e.g., Gupta & Bhaskar, 2023; Xie et al., 2024), together with our findings related to this factor, justify (to a large extent) our decision to include it in our model. Indeed, it directly impacted several constructs, namely Eff. exp. ($\beta = 0.60$, p

< 0.0, $f^2 = 0.53$), Perf. exp. ($\beta = 0.39$, $p < 0.001$, $f^2 = 0.13$), and Hed. mot. ($\beta = 0.22$, $p = 0.017$, $f^2 = 0.04$). It also exhibited indirect effects on Perf. exp. ($\beta = 0.13$, $p = 0.007$), Hed. mot. ($\beta = 0.29$, $p < 0.001$), and Beh. int. ($\beta = 0.36$, $p < 0.001$). The rather remarkable impact on effort expectancy, together with its effect on performance expectancy, aligns well with prior research, which demonstrated that individuals confident in their technological abilities tend to perceive tools as easier to operate and more beneficial (e.g., Tekin, 2024; Yang & Lou, 2024). Considering its direct and indirect effects on Hed. mot., we can argue that self-efficacy not only influences technical perceptions about imVR but also extends to beliefs about the pleasure derived from engaging with it. All in all, the multitude of direct and indirect effects allows us to theorize that self-efficacy plays a central role in the formation of educators' views and attitudes about imVR.

On the other hand, the absence of a direct relationship with behavioral intention contradicts prior evidence (e.g., Gupta & Bhaskar, 2023; Peng et al., 2024; Xie et al., 2024). One plausible explanation lies in the indirect pathways through which SE imVR influenced behavioral intention (via constructs such as effort expectancy, performance expectancy, and hedonic motivation). These findings highlight the mediating role of these factors in translating self-efficacy into concrete intentions (Yang & Lou, 2024).

Discussion of the Results Related to the Impact of Effort Expectancy (RH4a-d) and Performance Expectancy (RH5a-c)

Eff. exp. had statistically significant direct effects on Perf. exp. ($\beta = 0.22$, $p = 0.004$, $f^2 = 0.04$) and Habit ($\beta = -0.21$, $p = 0.030$, $f^2 = 0.03$), though the latter was negative. It showed no statistically significant direct effects on Hed. mot. or on Beh. int. The positive link we observed between Eff. exp. and Perf. exp. reinforces the argument that ease of use enhances users' perception of imVR's usefulness (C.-Q. Chen et al., 2024). The negative relationship between Eff. exp. and Habit suggests that once effort expectancy reaches a certain threshold, participants have a reduced need for repetitive usage patterns that underpin habit formation. Though this finding seems counterintuitive, we have to note that its statistical significance was not that strong, and the effect size was minimal. Nevertheless, further investigation is necessary to validate such assumptions.

The absence of a direct or indirect effect on Beh. int. is worthy of consideration. Marikyan and Papagiannidis (2022) suggested that ease of use carries less predictive power in prolonged or advanced stages of technology exposure; this might be the case in our study. Equally interesting is the fact that we found only an indirect impact of Eff. exp. on Hed. mot. through Perf. exp. ($\beta = 0.08$, $p = 0.007$). This finding implies that participants who deemed imVR easy to operate were more likely to perceive it as a performance-enhancing tool, which in turn increased the pleasure associated with its use.

We found that Perf. exp. positively influenced both Hed. mot. ($\beta = 0.37$, $p < 0.001$, $f^2 = 0.14$) and Beh. int. ($\beta = 0.17$, $p = 0.024$, $f^2 = 0.03$). Its significant impact on hedonic motivation marks it as a crucial antecedent to the enjoyment pre-service teachers derived from using imVR. In addition, we found that Hed. mot. mediated the effects of Perf. Exp. on Beh. int. ($\beta = 0.19$, $p < 0.001$). This indicates that the perceived usefulness of imVR not only directly influences the likelihood of adoption but also enhances the intrinsic enjoyment associated with its use, which in turn strengthens behavioral intention. Though it is difficult to link these results with past research (as the UTAUT-2 does not examine factor interactions), we have to note that several studies in the context of VE and imVR found that both performance expectancy and hedonic motivation have an impact on behavioral intention (e.g., Boel et al., 2023; Bower et al., 2020; Du & Liang, 2024; Xie et al., 2024). Considering this together with the findings of our study, we can support that the utilitarian benefits of a technology often intersect with its hedonic attributes.

The significant path to behavioral intention further confirms the centrality of performance expectancy in shaping technology adoption decisions (e.g., Kittinger & Law, 2024; J. Liu et al., 2025), including VR and imVR (Boel et al., 2023; Bower et al., 2020; Shen et al., 2019; Sumardani & Lin, 2024; Xie et al., 2024). Then again, there was no effect of performance expectancy on habit. This finding suggests that while pre-service teachers may recognize the potential of imVR to improve their teaching practices, this recognition does not necessarily translate into habitual usage behaviors (at least within the study's timeframe).

Discussion of the Results Related to the Impact of Hedonic Motivation and Habit (RH6a-b and RH7)

Hed. mot. had a statistically significant direct effect on Beh. int. ($\beta = 0.47$, $p < 0.001$, $f^2 = 0.28$). This relationship aligns with findings from prior studies, which have consistently identified enjoyment as a critical determinant of behavioral intention across various educational contexts and technologies, including VR and imVR (Boel et al., 2023; Bower et al., 2020; Sumardani & Lin, 2024; Xie et al., 2024). Therefore, we can conclude that the unique, engaging, and novel experiences offered by imVR likely influenced participants' behavioral intentions. Contrary to what we theorized, Hed. mot. had no effect on Habit. The absence of this relationship may reflect contextual factors specific to the study's participant sample. As the participants were engaged in a structured, task-oriented academic course, they may have been more susceptible to social influences (particularly the influence of the course instructor) and may have prioritized the conditions that enabled task completion over the development of habitual behaviors associated with pleasure. Indeed, both factors (Soc. inf. and Fac. cond.), were found to have a significant impact on Habit, as we discussed in a prior section.

We found that Habit had a statistically significant direct effect on Beh. int. ($\beta = 0.24$, $p < 0.001$, $f^2 = 0.10$). This finding aligns with previous research, which has recognized habit as a predictor of both behavioral intention and actual technology use (Barakat et al., 2025; J. Liu et al., 2025). In the context of imVR adoption, we can suggest that participants' repeated engagement with imVR-related tasks throughout the semester-long course may have facilitated the internalization of technology usage, reinforcing habitual behaviors. Age, sex, and prior experience did not have statistically significant effects on Habit, suggesting that the applicability of Habit spans across diverse cohorts of pre-service teachers. Thus, with the provision of appropriate organizational and technical support, even novices can potentially cultivate strong habitual behavioral patterns.

Discussion of the Results Related to the Impact of Age, Sex, and Experience (RH8, RH9, and RH10)

Contrary to our expectations, age did not demonstrate any statistically significant direct or indirect impact on any construct. While there are studies in which age played a role (e.g., Chang et al., 2019; Ning et al., 2019; Venkatesh et al., 2012), the absence of significant effects aligns with the body of literature challenging its role as a moderator, especially in the context of VR and imVR (e.g., Boel et al., 2023; Ogegbo et al., 2024). One plausible explanation lies in the study's participant demographics. The sample consisted of pre-service teachers, who are generally younger individuals (mean age = 21.56), and likely share similar levels of technological proficiency and exposure to imVR due to their structured coursework. This homogeneity may have minimized variation and dampened any moderating effects typically observed in more demographically diverse populations.

We hypothesized that sex would influence the model's constructs. However, we observed no such impact. Although previous studies have indicated the existence of sex differences in factors such as performance expectancy, social influence, and hedonic motivation (e.g., Chang et al., 2019; Ning et al., 2019; Venkatesh et al., 2012), our findings align with the research suggesting that, within the context of VR and imVR, demographic variables do not play a significant role or have only a marginal impact (e.g., Boel et al., 2023; Ogegbo et al., 2024; E. Y. Wang, Qian, et al., 2024). Again, a plausible explanation is the structured nature of pre-service teachers' exposure to imVR. Both male and female participants underwent formal training and hands-on activities designed to enhance their familiarity with imVR. Therefore, structured training interventions can reduce disparities in technology perception and usage across sexes.

Literature suggested that experience moderates the effects of other constructs, such as social influence and habit (Barakat et al., 2025; Chang et al., 2019; Venkatesh et al., 2012). However, our findings did not confirm these relationships, as we observed that it exerted only a statistically modest direct effect on SE imVR ($\beta = 0.17$, $p = 0.001$, $f^2 = 0.05$). This, indicates that participants with higher levels of imVR familiarity reported greater confidence in their ability to use this technology, supporting Bandura's (1977) argument that mastery experiences are a critical determinant of self-efficacy. Yet, given that we found no other direct or indirect effects, this can be viewed as a reflection of a boundary condition for its role: once participants have undergone structured training or received systematic exposure to imVR, the influence of prior technological experience diminishes. As participants reported a relatively low level of experience ($M = 2.04$, $SD = 1.02$), we can assume that this assertion holds true even if individuals do not reach a high level of proficiency in the use of imVR tools and applications.

Though the results regarding sex, age, and experience suggest a minimal impact of these factors, we suggest considering them in future research, as their role might be more pronounced in different contexts and demographic groups.

Discussion of the Results Related to the Model's In- and Out-of-Sample Predictive Power (H11)

We found that the adjusted R^2 value for Beh. int. was 0.63, meaning that 63% of the variance in this factor was explained. What is more, the variance in other constructs, such as Eff. exp. (Adj. R^2 = 0.59), Hed. mot. (Adj. $R^2 = 0.53$), and Perf. exp. (Adj. $R^2 = 0.53$) was also strongly explained. A reasonable level of explained variance was observed for constructs such as Habit (Adj. $R^2 = 0.36$) and SE imVR (Adj. $R^2 = 0.40$). These results allow us to assume that the model's in-sample explanatory power is more than satisfactory. The outcomes of the PLSpredict procedure established the model's out-of-sample predictive/explanatory power. As a result, we can conclude that the model is robust enough for predicting pre-service teachers' adoption behaviors in unseen data sets, indicating its utility in both theoretical and practical domains.

An explanation for the strong predictive and explanatory power of the proposed model is the integration of SE imVR as an antecedent construct. Its inclusion likely enhanced the model's accuracy, as evidenced by its strong direct effects on Eff. exp. ($\beta = 0.60$, $p < 0.001$, $f^2 = 0.53$) and performance expectancy ($\beta = 0.39$, $p < 0.001$, $f^2 = 0.13$). More importantly, because we revised the treatment of constructs and allowed for the exploration of hierarchical and cascading pathways between factors, this enhanced the model's explanatory depth. The inclusion of these effects not only advances theoretical understanding but also equips practitioners with deeper insights into how factors shape pre-service teachers' behavioral intention to use imVR.

As we stated in the Introduction, this study provided the ground for validating the model we initially proposed in a previous study. While the comparison of the results is beyond the scope of this study, and despite the initial testing being conducted in a different context (kindergarten in-service teachers and the general use of ICT tools), we affirm that the similarities between the two final models outnumber, by far, their differences (which can be attributed to variations in context). Thus, the model's confirmed generalizability allows us a reasonable degree of confidence in supporting its potential as a versatile framework for examining technology adoption across diverse educational contexts. The multitude of direct and indirect effects we observed further substantiates our assertion.

Discussion of the Results Related to Which Factors Should be Enhanced to Further Strengthen Participants' Behavioral Intention to Use imVR (RQ1)

The IPMA revealed habit, followed by hedonic motivation, as the factors necessitating targeted action because of their importance, coupled with their relative underperformance in shaping pre-service teachers' intention to use imVR. Given that prior research suggested that habit serves as a driver of sustained adoption (Söllner et al., 2024), we propose that teacher training programs should provide consistent and frequent opportunities for pre-service teachers to engage with imVR. Strategies may include semester-long coursework with imVR-based teaching assignments and the integration of imVR into routine lesson planning exercises. Additionally, the provision of support systems to facilitate habitual use (e.g., imVR labs and technical support) is essential. We also urge decision-makers to design systems that encourage routine usage.

Coming to hedonic motivation, we propose efforts to focus on improving the quality and richness of imVR experiences. Software developers should consider integrating enjoyable elements into their system designs to enhance enjoyment. Gamification, for instance, could offer opportunities to create positive user experiences, while aesthetically pleasing interfaces may boost overall enjoyment. Incorporating highly engaging, contextually relevant educational scenarios could enhance the pleasure derived from the technology. Additionally, leveraging feedback from pre-service teachers to refine imVR applications could further align their preferences and expectations with the immersive experiences offered. Nevertheless, given the hedonic motivation's secondary importance, such efforts should be viewed as supplementary.

Implications for Research and Practice

Our findings have significant implications for various stakeholders. Although for researchers, we will provide specific recommendations in the section on Limitations and Future Work, in this section, we focus on three aspects of our study that we consider important. First, our model illustrates the necessity of integrating constructs such as self-efficacy, habit, and hedonic motivation, which are not fully addressed in traditional behavioral intention frameworks. Second, we recommend experimental designs that pay attention to sample selection. As we argued in a preceding section, participants with little to no exposure to advanced technologies (such as imVR) are more likely to provide random or invalid responses when evaluating their perceptions and intentions. More importantly, our model highlights the necessity of suggesting and examining models that capture the complex and multifaceted dynamics of imVR adoption.

For institutions and policymakers, our findings highlight a multifaceted framework to facilitate the integration of imVR into teaching. The emphasis is on teacher education programs as they have the potential to play a significant role in shaping the future pedagogical landscape, particularly by addressing the attitudinal and motivational barriers evident in adopting advanced technologies like imVR. We found that self-efficacy acts as a critical determinant guiding pre-service teachers' intentions to utilize imVR in educational contexts. Its substantial influence on effort expectancy, performance expectancy, and hedonic motivation suggests that educational institutions must prioritize building confidence and competence among pre-service teachers in using imVR. In this respect, teacher education programs should consider incorporating professional development initiatives that focus on immersive technology, designed to bolster pre-service teachers' self-efficacy. These initiatives could include hands-on training, workshops, seminars, and collaborative projects that familiarize future educators with imVR both theoretically and practically. For instance, pre-service teachers can engage in collaborative projects that involve designing and implementing lessons that utilize imVR, creating opportunities for mastery experiences. Participatory professional development workshops, where pre-service teachers can observe and interact with experienced educators using imVR, can also enhance vicarious learning. Moreover, providing constructive feedback during and after these experiences can bolster self-efficacy, as individuals gain insight into their competencies and potential for success in using these technologies. Additionally, verbal persuasion from instructors and peers, coupled with assurance of continued technical support, can further reinforce pre-service teachers' confidence in their ability to utilize imVR.

The impact of habitual use in fostering pre-service teachers' intentions to integrate imVR we observed, necessitates that institutions develop semester-long courses with structured activities that consistently incorporate imVR. For example, pre-service teachers can be involved in projects that require them to utilize imVR in lesson plans and classroom simulations. By doing so, pre-service teachers are more likely to cultivate a habit of using this technology. Moreover, institutions can create supportive environments, such as dedicated imVR labs, where participants can interact with the technology outside of formal instructional time. Encouraging collaborative efforts among peers can also contribute to habit formation, as social interaction around technology use reinforces routine engagement, normalizing imVR as an integral component of their teaching toolkit. By making imVR a routine aspect of pre-service training, educators can begin to cultivate the habitual patterns necessary for sustained engagement with these technologies.

Moreover, the importance of hedonic motivation identified in our study indicates that teacher education programs should focus on creating enjoyable and engaging imVR experiences. This can be achieved through the incorporation of gamification elements into training modules, allowing pre-service teachers to experience the enjoyment associated with immersive learning environments. Additionally, the design of imVR applications should focus on user engagement, ensuring that they are aesthetically appealing and contextually relevant to educational objectives. Providing opportunities for creative exploration in imVR environments can also enhance intrinsic motivation, as pre-service teachers discover the joy of creating and interacting in virtual spaces. Feedback mechanisms that allow teachers to reflect on their experiences can further foster motivation, as the enjoyment associated with positive interactions with technology is reinforced.

Limitations and Future Work

Despite the interesting findings, our study is subject to certain limitations that must be considered. One limitation is the narrow demographic scope of the study sample, which consisted exclusively of senior pre-service teachers enrolled in a course specifically designed to address the educational uses of imVR. The structured educational environment, although it helped to address limitations of past research, does not reflect the diverse technological readiness and demographic composition of in-service teachers. The modified UTAUT-2 model we proposed allowed the examination of factor interactions and indirect effects; yet the scope of contextual factors was limited. We collected data at a single point in time; thus, we did not account for the long-term evolution of behavioral intentions. While we utilized validated instruments from UTAUT-2 and prior studies, self-reported measures are subject to bias, including social desirability bias. Participants may have over- or underestimated their actual self-efficacy, hedonic motivation, or behavioral intention, particularly since they were concluding a structured training course designed to reinforce imVR competencies.

To improve generalizability, we propose future studies to include a broader demographic samples that capture variations across age, sex, teaching experience, and technological exposure. A comparison between pre- and in-service teachers, as well as between early-career and veteran educators, would provide richer insights into the differential determinants of imVR adoption. Future research can also consider the expansion of our theoretical framework to include variables that better reflect the complexities of real-world educational settings. Then again, we advise caution as the addition of constructs will significantly increase the model's complexity. Conducting case studies in schools that implement imVR on an institutional scale could evaluate the interplay between individual factors (e.g., self-efficacy) and organizational support. Longitudinal studies are crucial for exploring sustained behavioral intentions and habit formation. They would allow researchers to examine temporal trends in moderating factors, such as changes in self-efficacy or facilitation over time as teachers gain experience and autonomy. Finally, to complement the quantitative findings, we suggest integrating mixed-methods approaches, as they could provide richer data on teachers' experiences with imVR.

CONCLUSION

In this study, we analyzed factors influencing pre-service teachers' intentions to imVR as an instructional tool, using a revised UTAUT-2 model. By incorporating self-efficacy and by examining hierarchical and indirect relationships between model variables, we addressed gaps in previous studies on imVR adoption in education. Our study contributes to the body of research on educators' adoption of imVR by demonstrating that:

- Hedonic motivation, performance expectancy, and habit are central drivers of behavioral intention to use imVR.
- Self-efficacy is a particularly influential factor, directly shaping pre-service teachers' perceptions of effort expectancy, performance expectancy, and hedonic motivation, key precursors to behavioral intention.
- Facilitating conditions strengthen self-efficacy, impact perceptions about imVR's ease of use, and promote habitual imVR use. Social influence has similar effects.
- Demographic factors such as age, sex, and prior experience have no or limited impact.
- There is a need for targeted intervention strategies, such as systematic exposure to imVR and efforts to enrich the pleasure derived from imVR experiences, to facilitate the adaptation of this technology by pre-service teachers.
- The suggested model exhibits strong predictive power both in-sample and out-of-sample, underscoring its utility as a reliable framework for understanding technology adoption in educational contexts.

In conclusion, our study shows that pre-service teachers' intention to use imVR is less driven by demographics and more by upstream levers that teacher preparation programs can directly shape, namely, self-efficacy built through facilitating conditions, sustained hands-on use that fosters habit, and enjoyable learning experiences that translate perceived usefulness into intention. For teacher education, this implies embedding imVR across coursework, with reliable infrastructure and support to cultivate confidence and routine use, while deliberately enhancing the hedonic quality of the experience. For technology-adoption research, our results argue for extending UTAUT-2 to model indirect pathways and to incorporate self-efficacy as a central antecedent, thereby offering stronger predictive power and a more realistic account of how intentions form in authentic preparation contexts.

STATEMENTS AND DECLARATIONS

- *Funding.* This research did not receive financial support.
- Competing interests. The authors declare that they have no conflicts of interest associated with this work.

- *Data availability.* The datasets generated or analyzed during the current study are available from the corresponding author upon reasonable request.
- *Institutional review board statement.* This study was carried out in accordance with all applicable legal requirements and institutional guidelines. The methodology and procedures were reviewed and approved by the Research and Ethics Committee of the Department of Primary Education at the University of the Aegean.
- *Informed consent statement.* All participants were volunteers who were fully informed about the study's procedures and their rights, including the option to withdraw from the study at any time. Informed consent was obtained from all participants, and their personal information was protected; no personal data was collected or processed.
- *Ethical statement.* The authors confirm that this manuscript is an original work developed independently, incorporating feedback from peer reviewers. This submission does not include

any findings previously published or authored by others, nor does it contain material or data generated by AI tools.

- *For language refinement and clarity*, the authors utilized Ghostwriter (an AI tool), after which they reviewed and edited the text, accepting complete responsibility for the final manuscript.

REFERENCES

Abdunool, K., Ali, M., Muhammad, S., & Warda, S. (2024). The mediating effect of behavioral intention in the relationship between social influence and wireless technology usage. *International Journal of Wireless & Mobile Networks, 16*(6), 37-46. https://doi.org/10.5121/ijwmn.2024.16603

Ajzen, I. (1991). Theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Almaiah, M. A., & Alyoussef, I. Y. (2019). Analysis of the effect of course design, course content support, course assessment and instructor characteristics on the actual use of E-learning system. *IEEE Access, 7*, 171907-171922. https://doi.org/10.1109/ACCESS.2019.2956349

Alotaibi, M. S. (2023). Factors influencing early childhood educators' use of digital educational aids: A sequential explanatory study. *Sage Open, 13*(4). https://doi.org/10.1177/21582440231217727

Antonopoulos, P., Fokides, E., & Koutromanos, G. (2025). Understanding learning and learning experience in immersive virtual reality. *Technology, Knowledge and Learning, 30,* 1771–1800. https://doi.org/10.1007/s10758-024-09764-z

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191-215. https://doi.org/10.1037/0033-295X.84.2.191

Barakat, A. M. M., Mahmoud, B. A. A., & Elneklawi, S. A. A. (2025). Preservice teachers' intentions to use social network sites: Adoption of Unified Theory of Acceptance and Use of Technology Model II. *International Journal of Instruction, 18*(1), 485-502. https://doi.org/10.29333/iji.2025.18126a

Barclay, D. W., Higgins, C. A., & Thompson, R. (1995). The partial least squares approach to causal modeling: Personal computer adoption and use as illustration. *Technology Studies, 2*(2), 285-309.

Boel, C., Rotsaert, T., Valcke, M., Rosseel, Y., Struyf, D., & Schellens, T. (2023). Are teachers ready to immerse? Acceptance of mobile immersive virtual reality in secondary education teachers. *Research in Learning Technology*, *31*, 2855. https://doi.org/10.25304/rlt.v31.2855

Bower, M., DeWitt, D., & Lai, J. W. M. (2020). Reasons associated with preservice teachers' intention to use immersive virtual reality in education. *British Journal of Educational Technology, 51*(6), 2215-2233. https://doi.org/10.1111/BJET.13009

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

Chang, C. M., Liu, L. W., Huang, H. C., & Hsieh, H. H. (2019). Factors influencing online hotel booking: Extending UTAUT2 with age, gender, and experience as moderators. *Information, 10*(9), 281. https://doi.org/10.3390/info10090281

Chen, C.-Q., Wang, C.-Y., Shan, X.-F., Zhan, L., & Chen, S.-J. (2024). An empirical investigation of reasons influencing pre-service teachers acceptance and rejection of immersive virtual reality usage. *Teaching and Teacher Education*, *137*, 104391. https://doi.org/10.1016/j.tate.2023.104391

Chen, G., Gully, S. M., & Eden, D. (2001). Validation of a new general self-efficacy scale. *Organizational Research Methods, 4*(1), 62-83. https://doi.org/10.1177/109442810141004

Chin, W. W. (1998). The partial least squares approach for structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295-336). Lawrence Erlbaum.

Chiu, C.-M., Wang, E. T. G., Fang, Y.-H., & Huang, H.-Y. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: The roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal, 24*(1), 85-114. https://doi.org/10.1111/j.1365-2575.2012.00407.x

Chuttur, M. Y. (2009). Overview of the Technology Acceptance Model: Origins, developments and future directions. *Working Papers on Information Systems, 9*(37), 9-37.

Cimperman, M., Brenčič, M. M., & Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior – Applying an extended UTAUT model. *International Journal of Medical Informatics, 90*, 22-31. https://doi.org/10.1016/j.ijmedinf.2016.03.002

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Academic Press. https://doi.org/10.4324/9780203771587

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, *22*(14), 1111-1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Du, W., & Liang, R.-y. (2024). Teachers' continued VR technology usage intention: An application of the UTAUT2 model. *Sage Open*, *14*(1). https://doi.org/10.1177/21582440231220112

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers, 21*, 719-734. https://doi.org/10.1007/s10796-017-9774-y

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods, 39*, 175-191. https://doi.org/10.3758/BF03193146

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

Fokides, E. (2023). Development and testing of a scale for examining factors affecting the learning experience in the Metaverse. *Computers & Education: X Reality, 2,* 100025. https://doi.org/10.1016/j.cexr.2023.100025

Fokides, E., & Antonopoulos, P. (2024). Development and testing of a model for explaining learning and learning-related factors in immersive virtual reality. *Computers & Education: X Reality, 4,* 100048. https://doi.org/10.1016/j.cexr.2023.100048

Fokides, E., & Giagiakou, E. (2025). Redefining, reconfiguring, and extending the UTAUT-2: A case study in the context of the use of ICT by kindergarten teachers. *Technology, Knowledge and Learning, 30,* 2175-2210. https://doi.org/10.1007/s10758-025-09895-x

Fransson, G., Holmberg, J., & Westelius, C. (2020). The challenges of using head mounted virtual reality in K-12 schools from a teacher perspective. *Education and Information Technologies, 25*(4), 3383-3404. https://doi.org/10.1007/s10639-020-10119-1

Guetz, B., & Bidmon, S. (2022). The impact of social influence on the intention to use physician rating websites: Moderated mediation analysis using a mixed methods approach. *Journal of Medical Internet Research, 24*(11), e37505. https://doi.org/10.2196/37505

Gupta, K. P., & Bhaskar, P. (2023). Teachers' intention to adopt virtual reality technology in management education. *International Journal of Learning and Change, 15*(1), 28-50. https://doi.org/10.1504/IJLC.2023.127719

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics, 1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hair, J. F., Jr., 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

Hair, J. F., Jr., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Jr., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2023). *Advanced issues in partial least squares structural equation modeling*. Sage.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In R. R. Sinkovics, & P. N. Ghauri (Eds.), *New challenges to international marketing* (pp. 277-319). Emerald Group. https://doi.org/10.1108/S1474-7979(2009)0000020014

Ikhlas, M., & Dela Rosa, E. D. (2023). Profile and predictors of high school teachers' attitude and self-efficacy in utilizing ICT: An investigation from Indonesia. *SN Social Sciences, 3*, Article 71. https://doi.org/10.1007/s43545-023-00654-2

Jang, J., Ko, Y., Shin, W. S., & Han, I. (2021). Augmented reality and virtual reality for learning: An examination using an extended technology acceptance model. *IEEE Access*, *9*, 6798-6809. https://doi.org/10.1109/ACCESS.2020.3048708

Khukalenko, I. S., Kaplan-Rakowski, R., An, Y., & Iushina, V. D. (2022). Teachers' perceptions of using virtual reality technology in classrooms: A large-scale survey. *Education and Information Technologies*, *27*(8), 11591-11613. https://doi.org/10.1007/s10639-022-11061-0

Kim, Y., Blazquez, V., & Oh, T. (2024). Determinants of generative AI system adoption and usage behavior in Korean companies: Applying the UTAUT model. *Behavioral Sciences, 14*(11), 1035. https://doi.org/10.3390/bs14111035

Kittinger, L. I., & Law, V. (2024). A systematic review of the UTAUT and UTAUT2 among K-12 educators. *Journal of Information Technology Education: Research*, *23*, Article 17. https://doi.org/10.28945/5246

Ko, Y., & Shin, W. S. (2023). Exploring teachers' intention to integrate technology: A comparison between online- and AR/VR-based instruction. *Technology, Pedagogy and Education, 32*(4), 537-554. https://doi.org/10.1080/1475939X.2023.2237037

Lazarus, R. S. (1991). *Emotion and adaptation*. Oxford Academic. https://doi.org/10.1093/oso/9780195069945.001.0001

Lee, H., & Hwang, Y. (2023). Training with, about, for Metaverse: A mixed methods research on training pre-service teachers as Metaverse-certified practitioners. *Journal of English Teaching through Movies and Media, 24*(4), 73-93. https://doi.org/10.16875/stem.2023.24.4.73

Liu, J., Dai, Q., & Chen, J. (2025). Factors affecting teachers' use of digital resources for teaching mathematical cultures: An extended UTAUT-2 model. *Education and Information Technologies, 30*(6), 7659-7688. https://doi.org/10.1007/s10639-024-13105-z

Liu, R., Wang, L., Koszalka, T. A., & Wan, K. (2022). Effects of immersive virtual reality classrooms on students' academic achievement, motivation and cognitive load in science lessons. *Journal of Computer Assisted Learning, 38*(5), 1422-1433. https://doi.org/10.1111/jcal.12688

Makransky, G., & Mayer, R. E. (2022). Benefits of taking a virtual field trip in immersive virtual reality: Evidence for the immersion principle in multimedia learning. *Educational Psychology Review, 34*(3), 1771-1798. https://doi.org/10.1007/s10648-022-09675-4

Marikyan, D., & Papagiannidis, S. (2022). Unified Theory of Acceptance and Use of Technology: A review. In S. Papagiannidis (Ed.), *TheoryHub book*. TheoryHub.

Menno, A. W. M., Simanjuntak, Y. I. W., & Linda, D. (2024). Overcoming self-efficacy challenges in teachers and prospective teachers: Key factors and solutions. *Indonesian Journal of Educational Research and Review, 7*(2), 285-297. https://doi.org/10.23887/ijerr.v7i2.77806

Narayan, J., & Naidu, S. (2024). A new contextual and comprehensive application of the UTAUT2 model post-COVID-19 pandemic in higher education. *Higher Education Quarterly, 78*(1), 47-77. https://doi.org/10.1111/hequ.12441

Narayanan, M., Ordynans, J. G., Wang, A., McCluskey, M. S., Elivert, N., Shields, A. L., & Ferrell, A. C. (2023). Putting the self in self-efficacy: Personal factors in the development of early teacher self-efficacy. *Education and Urban Society, 55*(2), 175-200. https://doi.org/10.1177/00131245211062528

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. *Computers and Education Open, 2*, 100041. https://doi.org/10.1016/j.caeo.2021.100041

Ning, F., Yang, Y., Zhu, T., Bayarmaa, T. I., & Ma, N. (2019). Influence of pre-service and in-service teachers' gender and experience on the acceptance of AR technology. *Foundations and Trends in Smart Learning: Proceedings of 2019 International Conference on Smart Learning Environments* (pp. 125-134). Springer. https://doi.org/10.1007/978-981-13-6908-7_18

Ogegbo, A. A., Penn, M., Ramnarain, U., Pila, O., Van Der Westhuizen, C., Mdlalose, N., Moser, I., Hlosta, M., & Bergamin, P. (2024). Exploring pre-service teachers' intentions of adopting and using virtual reality classrooms in science education. *Education and Information Technologies, 29*, 20299-20316. https://doi.org/10.1007/s10639-024-12664-5

Peng, R., Razak, R. A., & Halili, S. H. (2024). Exploring the role of attitudes, self-efficacy, and digital competence in influencing teachers' integration of ICT: A partial least squares structural equation modeling study. *Heliyon, 10*(13), e34234. https://doi.org/10.1016/j.heliyon.2024.e34234

Pottle, J. (2019). Virtual reality and the transformation of medical education. *Future Healthcare Journal, 6*(3), 181-185. https://doi.org/10.7861/fhj.2019-0036

Radianti, J., Majchrzak, T. A., Fromm, J., & Wohlgenannt, I. (2020). A systematic review of immersive virtual reality applications for higher education: Design elements, lessons learned, and research agenda. *Computers & Education, 147*, 103778. https://doi.org/10.1016/j.compedu.2019.103778

Rauch, W. (1979). The decision Delphi. *Technological Forecasting and Social Change, 15*(3), 159-169. https://doi.org/10.1016/0040-1625(79)90011-8

Rupp, M. A., Odette, K. L., Kozachuk, J., Michaelis, J. R., Smither, J. A., & McConnell, D. S. (2019). Investigating learning outcomes and subjective experiences in 360-degree videos. *Computers & Education, 128*, 256-268. https://doi.org/10.1016/j.compedu.2018.09.015

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13-35. https://doi.org/10.1016/j.compedu.2018.09.009

Shen, C.-W., Ho, J.-T., Ly, P. T. M., & Kuo, T.-C. (2019). Behavioural intentions of using virtual reality in learning: Perspectives of acceptance of information technology and learning style. *Virtual Reality, 23*, 313-324. https://doi.org/10.1007/s10055-018-0348-1

Söllner, M., Mishra, A. N., Becker, J. M., & Leimeister, J. M. (2024). Use IT again? Dynamic roles of habit, intention and their interaction on continued system use by individuals in utilitarian, volitional contexts. *European Journal of Information Systems, 33*(1), 80-96. https://doi.org/10.1080/0960085X.2022.2115949

Sumardani, D., & Lin, C. H. (2024). Investigating the factors that influence the implementation of virtual reality in science learning. *Jurnal Pendidikan IPA Indonesia, 13*(1), 76-89. https://doi.org/10.15294/jpii.v13i1.44018

Tamilmani, K., Rana, N. P., Dwivedi, Y. K., & Sahu, G. P. (2021). The extended Unified Theory of Acceptance and Use of Technology (UTAUT2): A systematic literature review and theory evaluation. *International Journal of Information Management, 57*, 102269. https://doi.org/10.1016/j.ijinfomgt.2020.102269

Tekin, Ö. G. (2024). Factors affecting teachers' acceptance of artificial intelligence technologies: Analyzing teacher perspectives with structural equation modeling. *Instructional Technology and Lifelong Learning, 5(*2), 399-420.

Teo, T. (2009). Modelling technology acceptance in education: A study of pre-service teachers. *Computers & Education, 52*(2), 302-312. https://doi.org/10.1016/j.compedu.2008.08.006

Tondeur, J. (2020). Teachers' pedagogical beliefs and technology use. In M. Peters (Ed.), *Encyclopaedia of teacher education* (pp. 1-5). Springer. https://doi.org/10.1007/978-981-13-1179-6_111-1

Tseng, T. H., Lin, S., Wang, Y. S., & Liu, H. X. (2022). Investigating teachers' adoption of MOOCs: The perspective of UTAUT2. *Interactive Learning Environments, 30*(4), 635-650. https://doi.org/10.1080/10494820.2019.1674888

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

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

Wang, E. Y., Qian, D., Zhang, L., Li, B. S.-K., Ko, B., Khoury, M., Renavikar, M., Ganesan, A., & Caruso, T. J. (2024). Acceptance of virtual reality in trainees using a technology acceptance model: Survey study. *JMIR Medical Education, 10*, e60767. https://doi.org/10.2196/60767

Wang, Y., Pradubwate, R., & Sirawong, N. (2024). Factors affecting the use of ICT by teachers at Nan Yang Technician College, China. *International Journal of Sociologies and Anthropologies Science Reviews, 4*(6), 543-552. https://doi.org/10.60027/ijsasr.2024.4940

Wang, Y.-Y., & Chuang, Y.-W. (2024). Investigating the potential adverse effects of virtual reality-based learning system usage: From UTAUT2 and PPVITU perspectives. *Interactive Learning Environments, 32*(9), 5106-5125. https://doi.org/10.1080/10494820.2023.2209790

Wu, D., Zhou, C., Meng, C., & Chen, M. (2020). Identifying multilevel factors influencing ICT self-efficacy of K-12 teachers in China. In S. Cheung, R. Li, K. Phusavat, N. Paoprasert, & L. Kwok (Eds.), *Blended Learning. Education in a Smart Learning Environment* (pp. 303-314). Springer. https://doi.org/10.1007/978-3-030-51968-1_25

Xie, Y., Wan, C., & Kong, K. (2024). Factors influencing Chinese pre-service teachers' behavioral intention and use behavior to adopt VR training system: Based on the UTAUT2 model. *Humanities and Social Sciences Communications, 11*, Article 1300. https://doi.org/10.1057/s41599-024-03832-6

Yang, J., & Lou, K. (2024). Exploring the nexus of self-efficacy in digital literacy and technology acceptance: Insights from L2 Chinese teachers. *Asia Pacific Journal of Education*, *2024*, 1-19. https://doi.org/10.1080/02188791.2024.2336247

Zhao, J., Lin, L., Sun, J., & Liao, Y. (2020). Using the summarizing strategy to engage learners: Empirical evidence in an immersive virtual reality environment. *The Asia-Pacific Education Researcher, 29*, 473-482. https://doi.org/10.1007/s40299-020-00499-w

APPENDIX A

The study's questionnaire. The items were presented in random order.

Part 1 [adapted from Venkatesh et al.'s (2012) paper]

Performance expectancy

I find imVR useful for my teaching practices.

Using imVR will allow me to complete my teaching tasks more efficiently.

imVR can boost my productivity in the classroom.

Effort expectancy

Learning how to use imVR applications and hardware is easy for me.

I find my interaction with imVR applications and hardware to be simple.

imVR applications and hardware are user friendly.

It is easy for me to become skillful at using imVR applications and hardware.

Perceived social influence

People who are important to me believe that I should use imVR for educational purposes.

Those who influence my professional behavior suggest that I should use imVR in my teaching practices.

People whose views I value recommend using imVR in my teaching.

Perceived facilitating conditions

I believe that I will have access to the resources needed to effectively use imVR in my teaching.

I have the necessary knowledge to use imVR in my educational activities.

imVR is compatible with other tools that I intend to use while teaching.

I am positive in receiving help from other colleagues if I encounter problems related to the use of imVR in my teaching.

Hedonic motivation

I believe that using imVR in my teaching will be fun.

I believe that using imVR in my teaching will give me pleasure.

Integrating imVR into my teaching will be an engaging practice for me.

Habit

The use of imVR has become routine for me.

I use imVR for educational purposes on a daily basis.

I am almost addicted to using imVR.

Behavioral intention to use or continue using imVR

In my teaching activities, the use of imVR will be an integral part.

I will make every effort to integrate imVR into my daily teaching activities.

I plan to use imVR frequently in my educational pursuits.

Part 2 [adapted from Chen et al.'s (2001) paper]

Self-efficacy in imVR

I will be able to achieve most of the educational goals I have set using imVR.

If I encounter difficulties related to the use of imVR, I am confident that I will overcome them successfully.

In general, I believe that I will be able to leverage imVR to achieve results that are important to my educational goals.

I believe that I will be able to achieve almost every educational goal I set using imVR.

I am able to successfully overcome challenges that will arise when using imVR in educational environments.

I am confident in my ability to excel in a wide range of educational tasks that will require the use of imVR.

Compared to other colleagues, I can use imVR more effectively.

Even if challenges arise, I will effectively fulfill my teaching tasks using imVR.

APPENDIX B

Table B1. Items' loadings

Items	Factors							
	Beh. int.	Eff. exp.	Fac. cond.	Habit	Hed. mot.	Perf. exp.	SE imVR	Soc. inf.
Beh. int1	0.95							
Beh. int2	0.95							
Beh. int3	0.95							
Eff. exp1		0.88						
Eff. exp2		0.84						
Eff. exp3		0.80						
Eff. exp4		0.86						
Fac. cond1			0.70					
Fac. cond2			0.83					
Fac. cond3			0.81					
Fac. cond4			0.61					
Hab1				0.87				
Hab2				0.94				
Hab3				0.94				
Hed. mot1					0.94			
Hed. mot2					0.96			
Hed. mot3					0.94			
Perf. exp1						0.90		
Perf. Exp2						0.89		
Perf. Exp3						0.89		
SE imVR1							0.75	
SE imVR2							0.76	
SE imVR3							0.82	
SE imVR4							0.79	
SE imVR5							0.83	
SE imVR6							0.79	
SE imVR7							0.67	
SE imVR1							0.79	
Soc. inf1								0.88
Soc. inf2								0.89
Soc. inf3								0.94

Note. The highlighted rows indicate lower than 0.70 loadings

Table B2. Internal consistency, reliability, and convergent validity

Factor	Cronbach's α	Composite reliability (rho_A)	AVE
Beh. int.	0.94	0.94	0.90
Eff. exp.	0.87	0.87	0.72

Factor	Cronbach's α	Composite reliability (rho_A)	AVE
Fac. cond.	0.72	0.73	0.55
Habit	0.91	0.91	0.84
Hed. mot.	0.94	0.94	0.90
Perf. exp.	0.87	0.87	0.79
SE imVR	0.91	0.91	0.60
Soc. inf.	0.89	0.89	0.82

Table B3. Discriminant validity (HTMT analysis)

	Age	Beh. int.	Eff. exp.	Exp.	Fac. cond.	Habit	Hed. mot.	Perf. exp	SE imVR	Sex	Soc. inf.
Age											
Beh. int.	0.02										
Eff. exp.	0.04	0.61									
Exp.	0.07	0.06	0.03								
Fac. cond.	0.08	0.71	0.78	0.11							
Habit	0.03	0.53	0.29	0.06	0.65						
Hed. mot.	0.03	0.77	0.67	0.03	0.64	0.31					
Perf. exp.	0.02	0.72	0.72	0.05	0.71	0.40	0.75				
SE imVR	0.07	0.64	0.82	0.09	0.73	0.41	0.70	0.78			
Sex	0.05	0.04	0.02	0.31	0.07	0.08	0.06	0.11	0.06		
Soc. inf.	0.10	0.42	0.32	0.06	0.51	0.52	0.41	0.43	0.46	0.05	

Table B4. Multicollinearity diagnostics

Item	VIF
Beh. int1	4.53
Beh. int2	4.39
Beh. int3	4.41
Eff. exp1	2.53
Eff. exp2	2.12
Eff. exp3	1.73
Eff. exp4	2.31
Fac. cond1	1.47
Fac. cond2	1.73
Fac. cond3	1.71
Fac. cond4	1.14
Hab1	2.05
Hab2	5.23
Hab3	4.97
Hed. mot1	4.31
Hed. mot2	5.06

Item	VIF
Hed. mot3	3.98
Perf. exp1	2.40
Perf. Exp2	2.32
Perf. Exp3	2.21
SE imVR1	2.05
SE imVR2	2.10
SE imVR3	2.45
SE imVR4	2.31
SE imVR5	2.70
SE imVR6	2.33
SE imVR7	1.83
SE imVR8	2.22
Soc. inf1	2.39
Soc. inf2	2.53
Soc. inf3	3.42

Note. The highlighted rows indicate VIF values higher than 5.0

APPENDIX C

Table C1. The results of the PLS-SEM, direct effects

Path	*t*	*p*	*β*	*f*²	Interpretation
Age -> Beh. int.	0.89	0.375	0.03	0.00	-
Age -> Eff. exp.	0.97	0.334	-0.06	0.01	-
Age -> Fac. cond.	0.19	0.846	-0.02	0.00	-
Age -> Habit	0.30	0.763	-0.01	0.00	-
Age -> Hed. mot.	0.35	0.724	-0.02	0.00	-
Age -> Perf. exp.	0.42	0.677	-0.02	0.00	-
Age -> SE imVR	0.82	0.413	0.06	0.01	-
Age -> Soc. inf.	0.70	0.485	-0.05	0.00	-
Eff. exp. -> Beh. int.	0.77	0.443	0.05	0.00	-
Eff. exp. -> Habit	2.17	0.030	-0.21	0.03	Modest path, small effect
Eff. exp. -> Hed. mot.	1.92	0.054	0.15	0.02	-
Eff. exp. -> Perf. exp.	2.87	0.004	0.22	0.04	Modest path, small effect
Exp. -> Beh. int.	1.14	0.253	0.05	0.01	-
Exp. -> Eff. exp.	1.04	0.297	-0.06	0.01	-
Exp. -> Fac. cond.	1.11	0.265	-0.08	0.01	-
Exp. -> Habit	1.12	0.261	0.07	0.01	-
Exp. -> Hed. mot.	0.75	0.456	-0.04	0.00	-
Exp. -> Perf. exp.	1.21	0.227	0.06	0.01	-
Exp. -> SE imVR	3.25	0.001	0.17	0.05	Modest path, small effect
Exp. -> Soc. inf.	1.08	0.281	-0.08	0.01	-
Fac. cond. -> Beh. int.	1.57	0.116	0.12	0.02	-
Fac. cond. -> Eff. exp.	5.22	< 0.001	0.31	0.15	Moderate path, medium effect
Fac. cond. -> Habit	5.54	< 0.001	0.47	0.18	Moderate path, medium effect
Fac. cond. -> Hed. mot.	0.59	0.556	0.06	0.00	-
Fac. cond. -> Perf. exp.	2.16	0.031	0.16	0.03	Modest path, small effect
Fac. cond. -> SE imVR	7.29	< 0.001	0.51	0.37	Strong path, large effect
Habit -> Beh. int.	4.48	< 0.001	0.24	0.10	Modest path, small effect
Hed. mot. -> Beh. int.	6.51	< 0.001	0.47	0.28	Moderate path, medium effect
Hed. mot. -> Habit	0.89	0.372	-0.08	0.00	-
Perf. exp. -> Beh. int.	2.26	0.024	0.17	0.03	Modest path, small effect
Perf. exp. -> Habit	1.16	0.247	0.10	0.01	-
Perf. exp. -> Hed. mot.	4.58	< 0.001	0.37	0.14	Moderate path, small effect
SE imVR -> Beh. int.	0.26	0.793	-0.02	0.00	-
SE imVR -> Eff. exp.	9.88	< 0.001	0.60	0.53	Strong path, large effect
SE imVR -> Habit	1.11	0.266	0.12	0.01	-
SE imVR -> Hed. mot.	2.38	0.017	0.22	0.04	Modest path, small effect
SE imVR -> Perf. exp.	4.74	< 0.001	0.39	0.13	Moderate path, small effect
Sex -> Beh. int.	0.68	0.499	-0.03	0.00	-
Sex -> Eff. exp.	0.96	0.337	-0.05	0.01	-

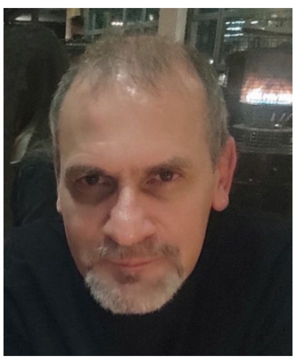
Path	*t*	*p*	*β*	*f*²	Interpretation
Sex -> Fac. cond.	0.46	0.648	0.03	0.00	-
Sex -> Habit	1.30	0.194	-0.07	0.01	-
Sex -> Hed. mot.	0.02	0.981	0.00	0.00	-
Sex -> Perf. exp.	1.83	0.068	0.10	0.02	-
Sex -> SE imVR	1.30	0.193	0.07	0.01	-
Sex -> Soc. inf.	0.93	0.352	-0.07	0.00	-
Soc. inf. -> Beh. int.	0.36	0.722	-0.02	0.00	-
Soc. inf. -> Eff. exp.	1.85	0.064	-0.10	0.02	-
Soc. inf. -> Habit	3.59	< 0.001	0.28	0.09	Modest path, small effect
Soc. inf. -> Hed. mot.	1.17	0.242	0.08	0.01	-
Soc. inf. -> Perf. exp.	1.67	0.095	0.09	0.02	-
Soc. inf. -> SE imVR	3.44	0.001	0.22	0.07	Modest path, small effect

Table C2. The results of the PLS-SEM, indirect effects

Path	*t*	*p*	*β*	Interpretation
Age -> Beh. int.	0.36	0.717	-0.03	-
Age -> Eff. exp.	0.40	0.691	0.02	-
Age -> Habit	0.19	0.852	-0.01	-
Age -> Hed. mot.	0.18	0.859	-0.01	-
Age -> Perf. exp.	0.03	0.979	0.00	-
Age -> SE imVR	0.32	0.746	-0.02	-
Eff. exp.-> Beh. int.	1.81	0.071	0.10	-
Eff. exp.-> Habit	0.16	0.871	0.00	-
Eff. exp.-> Hed. mot.	2.69	0.007	0.08	Weak path
Exp. -> Beh. int.	0.22	0.823	0.01	-
Exp. -> Eff. exp.	0.92	0.360	0.05	-
Exp. -> Habit	0.78	0.436	-0.04	-
Exp. -> Hed. mot.	0.79	0.432	0.04	-
Exp. -> Perf. exp.	0.44	0.662	0.02	-
Exp. -> SE imVR	1.25	0.210	-0.06	-
Fac. cond. -> Beh. int.	6.60	< 0.001	0.41	Moderate path
Fac. cond. -> Eff. exp.	6.43	< 0.001	0.31	Moderate path
Fac. cond. -> Habit	0.95	0.342	-0.06	-
Fac. cond. -> Hed. mot.	4.70	< 0.001	0.39	Moderate path
Fac. cond. -> Perf. exp.	5.84	< 0.001	0.34	Moderate path
Hed. mot. -> Beh. int.	0.84	0.402	-0.02	-
Perf. exp. -> Beh. int.	4.30	< 0.001	0.19	Modest path
Perf. exp. -> Habit	0.87	0.386	-0.03	-
SE imVR -> Beh. int.	5.34	< 0.001	0.36	Moderate path
SE imVR -> Habit	1.68	0.093	-0.12	-
SE imVR -> Hed. mot.	4.40	< 0.001	0.29	Modest path

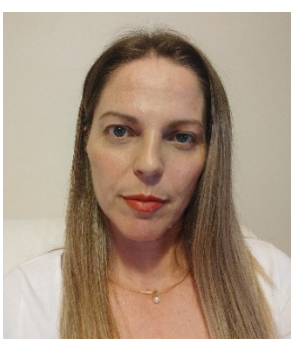
Path	t	p	β	Interpretation
SE imVR -> Perf. exp.	2.71	0.007	0.13	Modest path
Sex -> Beh. int.	0.67	0.502	0.04	-
Sex -> Eff. exp.	1.07	0.285	0.06	-
Sex -> Habit	0.23	0.815	0.01	-
Sex -> Hed. mot.	1.11	0.269	0.06	-
Sex -> Perf. exp.	0.56	0.574	0.03	-
Sex -> SE imVR	0.05	0.961	0.00	-
Soc. inf. -> Beh. int.	3.94	< 0.001	0.19	Modest path
Soc. inf. -> Eff. exp.	3.09	0.002	0.13	Modest path
Soc. inf. -> Habit	0.77	0.441	0.02	-
Soc. inf. -> Hed. mot.	2.60	0.009	0.12	Modest path
Soc. inf. -> Perf. exp.	2.30	0.022	0.09	Weak path

AUTHORS



Dr Emmanuel Fokides is an Associate Professor at the Department of Primary Education, University of the Aegean, Greece. His courses focus on the educational uses of emerging technologies, virtual reality, digital storytelling, augmented reality, and serious games. Since 1994, he has been involved in a number of research projects regarding distance and lifelong learning and the educational uses of virtual and augmented reality. He is also the founder of the Emerging Technologies in Education initiative (ETiE). His work is published in several conference proceedings, chapters in edited books, and journals. He is also the co-author of three books.

.



Ms Maria Daskalou holds two bachelor's degrees, one in Mediterranean studies and one in education. She is currently pursuing an M.A. in the field of education. As a new researcher, her interests lie in the use of technology in education, focusing on immersive virtual reality. She is a passionate advocate of using technology as an important tool during the educational process to stimulate the interest of students.