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Research article

Unlocking future learning: Exploring higher education students' intention to adopt meta-education

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ABSTRACT

Despite the potential of meta-education to transform higher education, there remains a scarcity of research investigating students' adoption intentions. This study aimed to identify factors influencing students' intentions to adopt meta-education using an extended Decomposed Theory of Planned Behavior model (DTPB). Data was collected via an online survey of 596 higher education students from Jordan who were purposefully selected. Structural equation modeling using partial least squares analysis revealed attitude, social influence, and perceived behavioral control as key antecedents of adoption intention. Furthermore, newly added variables including perceived enjoyment, herd behavior, student autonomy, and student innovativeness showed efficiency in explaining variance in attitude, social influence, and perceived behavioral control. Overall, the extended model provided meaningful insights on factors driving students' willingness to adopt meta-education. The study contributes to theory by extending the decomposed TPB model in the context of emerging educational technologies. It also provides practical implications for policymakers and educators aiming to encourage meta-education adoption.

1. Introduction

In past years, the educational field has witnessed a substantial transformation through the rise of innovative technologies. Meta-education (or metaverse-based education) is one of the novel technologies that has gained significant attention [1]. Meta-education involves the utilization of virtual reality (VR) and augmented reality (AR) technologies to create immersive and interactive learning environments [2]. Metaverse offers unique opportunities for higher education institutions (HEIs) to enhance the learning experience and engage students in novel and exciting manners.

In 2020, the educational processes around the globe have been widely disrupted by the COVID-19 pandemic. Consequently, a rapid shifting towards more remote learning approaches has significantly enabled educational continuity during widespread lockdowns [3].

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As a result, the emergence of the metaverse has presented opportunities to develop a new educational ecosystem [4]. The metaverse is an immersive three-dimensional virtual environment where users engage in social and economic interactions facilitated by technology, regardless of physical location [5]. Metaverse environments provide immersive, interactive experiences that engage students in ways traditional classrooms cannot [2]. In fact, the metaverse concept initially emerged in fiction, where users acquired virtual identities (i.e., avatars) to simulate interactions with other users across everyday situations [6].

Unlike other educational technologies, the metaverse offers a distinctive combination of interactivity, embodied experience, and persistence [6]. In metaverse-based platforms, students are highly engaged in interactive learning environments. These environments enable dynamic and innovative educational settings that support autonomous and collaborative learning with access to diverse resources. In particular, the metaverse operates independently of users' physical movements, ensuring seamless connection without time limitations. The embodied experience introduces avatars that transcend physical constraints, heightening realism within the virtual environment comparable to 3D games. Lastly, persistence preserves conversations, data, and objects even after users log off, maintaining valuable information for later analysis [7].

The educational sector stands out as one of the most promising and imminent applications of the metaverse. However, it is argued that human behaviors in the metaverse should be investigated in an educational environment to determine how it differs from behavior in the actual world [8]. This necessitates the development of new management and organizational leadership models [5]. Specifically, the industry and business sectors require a well-educated workforce that can adapt to the challenges presented by the metaverse environment. To address limited access to hands-on learning in traditional classrooms, HEIs can leverage virtual reality platforms that enable immersive real-world experiences. Unlike traditional classrooms, metaverse environments have no physical constraints that allow students to easily interact with academic staff in a virtual setting. Hence, the metaverse functions as a virtual world that emulates a real university, enabling hybrid and collaborative learning experiences [6].

Educational implementation of the metaverse remains nascent, constrained by limited integration of AI-enabled adaptive systems and IoT for immersive virtual interactions [4]. Adoption involves opportunities and challenges for HEIs, policymakers, instructors, and students. Evaluating how HEIs, which cultivate educational and social values, adapt to serve modern students is critical. Effectively transitioning to the metaverse ensures their continued relevance in the digital era. Adequate implementation is required for HEIs to enhance teaching quality using metaverse technology. While top management and policymakers determine metaverse deployment, success hinges on students. This emphasizes the relevance of student viewpoint research for institutional adoption initiatives. Hence, successful adoption of the metaverse in higher education necessitates identifying key drivers of student acceptance. Gaining student perspectives to elucidate critical adoption factors will inform institutional strategies to facilitate metaverse integration.

Over the past few years, the integration of education-based technologies in Jordan has received considerable attention as a mean to improve the quality and accessibility of education [9,10]. Existing literature points to a lack of widespread implementation of immersive technologies in organizational and individual settings across developing countries. This gap is due to the limited presence of rigorous empirical research examining their utilization [11]. Supporting this, empirical studies in developing countries (e.g., Jordan) that investigate the factors influencing the adoption of immersive technologies (e.g., metaverse, AR, VR) in higher education is dearth [12]. Hence, further research is necessary to understand adoption behavior and offer evidence-based strategies for successful implementation of immersive educational technologies in developing countries.

This study is conducted in response to the growing need for research on immersive technologies in education. It primarily focuses on identifying and empirically investigating the key factors influencing higher education students' intentions to adopt meta-education. This study uncovers the main attitudinal, social, and behavioral beliefs that influence students' adoption intention towards meta-education. To achieve this objective, it presents a modified version of "The Decomposed Theory of Planned Behavior (DTPB) Model" [13]. As a result, this study makes a substantial contribution to education and technology adoption. Addressing the dearth of research on the adoption of meta-education by higher education students is one of its major contributions. It investigates a variety of belief-related factors to understand the cognitive and motivational aspects that influence students' intentions in adopting meta-education. Through a comprehensive analysis of these factors, valuable insights are provided to guide the development and implementation of meta-education programs. Policymakers of HEIs must be informed of the variables that influence students' intent to employ meta-education. Contributing to the body of knowledge regarding the application of technology in higher education, this understanding will assist HEIs in developing engaging and productive learning environments for students. The emphasis is placed on the context of meta-education, as opposed to a more general examination of technology adoption. Through the implementation of a context-specific analysis, a more comprehensive overview is obtained giving the unique aspects with particular significance and influence in the process of adopting meta-education.

The results of this study not only contribute to the existing body of knowledge on the technology adoption in higher education but also offer valuable suggestions for administrators, policymakers, and educators who aim to integrate meta-education into their academic programs. A thorough analysis of the factors that influence the inclination of students towards adopting meta-education informs the development of these recommendations. Furthermore, the practical implications of this work go beyond just individual educational institutions. They inform and contribute to larger discussions and initiatives surrounding the adoption of innovative technologies across education. Hence, the research adds to the ongoing efforts aimed at improving educational practices and enhancing learning outcomes.

This paper is structured as follows: first, the theoretical framework underlying this research is outlined; second, a model is presented that proposes relationships between factors impacting meta-education adoption; third, the results of hypothesis testing are reported; fourth, the implications of the findings are deliberated; finally, the primary conclusions and contributions of this study are highlighted.

2. Theoretical foundation: the decomposed theory of planned behavior

While several models exist for predicting IT adoption intentions [14], the Theory of Planned Behavior (TPB) [15], and its extension, the Decomposed Theory of Planned Behavior (DTPB) [13] have gained significant traction. Both models showcase their effectiveness in anticipating technology adoption across various domains [16]. However, TPB stands out for its dual capacity in accurately forecasting and efficiently facilitating behavior modification [17]. This makes it a versatile tool for understanding and influencing IT adoption intentions.

The DTPB has several advantages over other models such as the "Technology Acceptance Model" (TAM) [18], and the "Unified Theory of Acceptance and Use of Technology" (UTAUT) [19]. This assertion remains valid, especially when examining students' intentions to adopt novel meta-cognitive learning strategies. Although TAM and UTAUT offer valuable frameworks, their initial purpose was to elucidate the adoption of concrete technologies, not meta-education, or other complex technologies [20]. As an alternative,

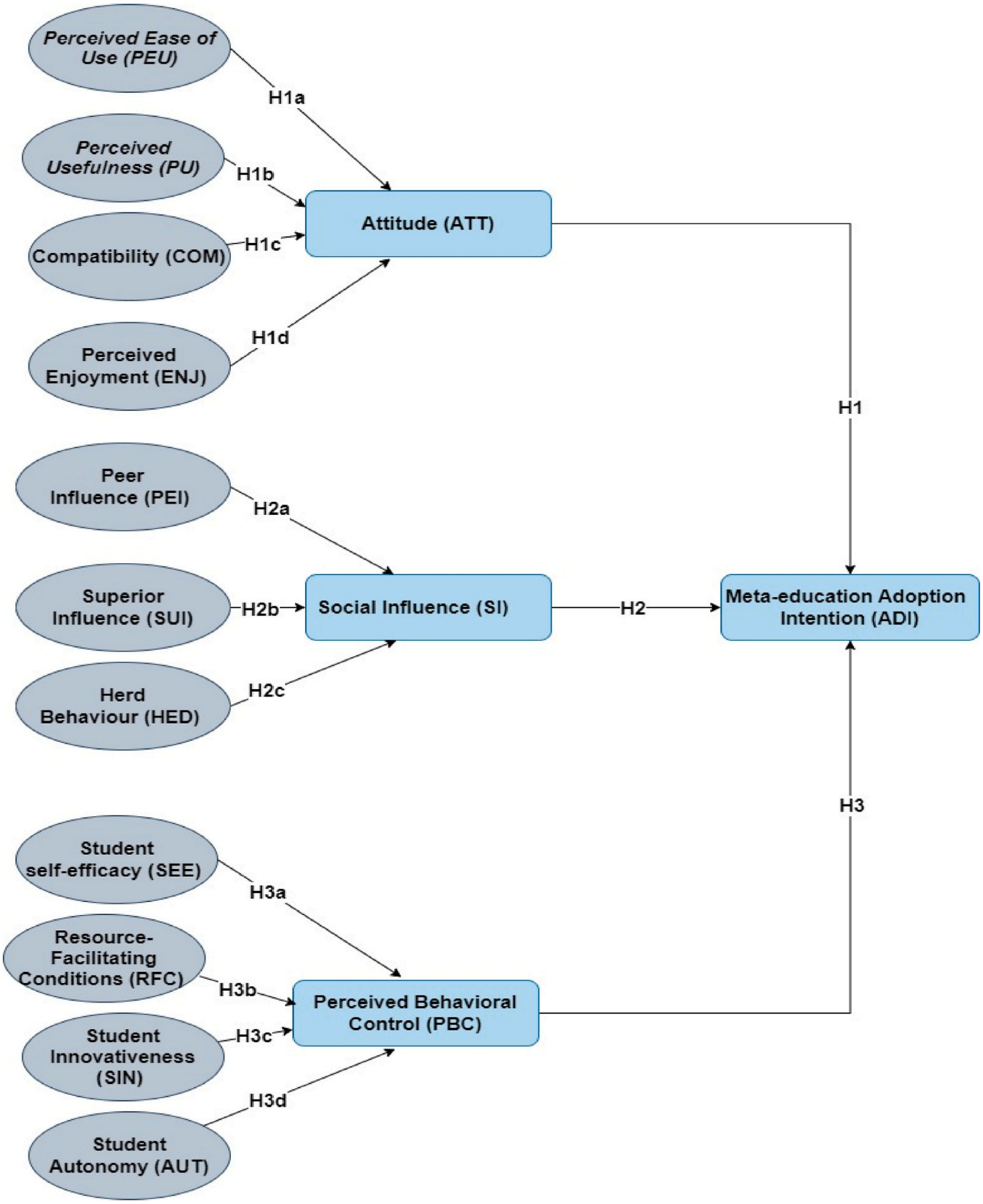

Fig. 1. Research model.

DTPB is designed to explain the motivations that underpin novel skill-based systems. Moreover, DTPB explores critical elements such as attitude, social norm, and perceived control into constructs with multiple dimensions. This provides greater predictive power than the TAM/UTAUT factors that are more general in nature [13]. This also helps isolate the most impactful levers of students' meta-education adoption. Also, DTPB integrates essential predictors like peer influence and compatibility lacking in TAM/UTAUT models. This provides a more comprehensive framework versus technology-centric model.

Unlike the TAM model, which does not include social influences in its core structure, TPB accommodates social norms within its model. Furthermore, TPB offers a more comprehensive perspective than the UTAUT model [19] through incorporating the crucial attitude variable. This is significant because attitude significantly influences the behavioral intention to adopt a specific technology. Another advantage of TPB is the assumption that individuals have deliberate control over their intended actions. This is influenced by resource availability such as ability, time, information, and financial means [15]. Remarkably, TPB acknowledges the confines in explaining behaviors lying beyond individual control—an aspect not comprehensively addressed by TAM and UTAUT. Overall, DTPB's decomposition of key factors and inclusion of additional variables equip it to fully explain and predict students' motivations to adopt new meta-cognitive learning strategies versus relying on more generic technology adoption models.

The DTPB builds on the original TPB. This posits that behavior is determined by intentions, which are influenced by attitudes (ATT) toward the behavior, subjective norms (SN), and perceived behavioral control (PBC) [17]. Nevertheless, TPB falls short in identifying the antecedents of these main factors. In response, Taylor and Todd [13] presented the DTPB as a modified version of the TPB. Taylor and Todd [13] argued that the TPB constructs could be enhanced by breaking them into more specific, multidimensional belief structures, thus allowing for a more nuanced understanding of the antecedents of intention and behavior. Consequently, the DTPB offers an enhanced comprehension of complex behavioral dynamics and provides greater explanatory power than the original TPB model [21,22].

The DTPB extends the TPB by distinguishing between attitudinal, normative, and control beliefs into distinct subdivisions, using existing theories as support. However, in DTPB, attitudinal beliefs are broken down into perceived usefulness, compatibility, and ease of use, based on innovation diffusion theory [23] Normative beliefs are divided into peer and superior influences based on interpersonal behavior theory [24]. Control beliefs are decomposed into self-efficacy and resource-facilitating conditions, drawing from self-efficacy theory [25]. Taylor and Todd [13] demonstrate that this decomposed model of the TPB provides a better understanding of complex behavioral dynamics and offers greater explanatory power than the original TPB model.

Overall, the DTPB presents a valuable framework for understanding and predicting the adoption of new technologies like the metaverse. It builds upon the established TPB by elaborating the components that shape behavioral intentions. In particular, the DTPB examines individuals' attitudes, subjective norms, and perceived behavioral control related to embracing the metaverse. This granular inspection of the underlying drivers of technology acceptance facilitates a nuanced analysis of the psychological and social influences that may either facilitate or impede metaverse adoption. The detailed perspective afforded by the DTPB enables the pinpointing of specific perceptions, beliefs, and pressures that impact intentions to adopt the metaverse. Identifying these salient factors creates opportunities to craft targeted interventions to shape attitudes and social norms in ways that promote integration of the metaverse. Accordingly, applying the decomposed framework of the DTPB holds significant potential for gaining a sophisticated understanding of metaverse acceptance and steering its uptake through evidence-based strategies.

2.1. Modifying the DTPB

This adaptation of the DTPB aims to further investigate students' inclination for using the metaverse as a learning tool. It considers the particular features of meta-education platforms (see Fig. 1). It aims to uncover the various factors that impact students' adoption intention of these platforms for educational purposes.

The first modification involves incorporating the concept of perceived enjoyment as a key antecedent to attitudes [26]. Perceived enjoyment refers to the subjective experience of pleasure or satisfaction that individuals perceive when engaging with a particular technology or system. Recent research has investigated the role of perceived enjoyment in shaping students' attitudes toward educational technology acceptance and use [27,28]. This work recognizes that students' attitudes regarding technology for learning are informed not just by perceptions of usefulness or ease of use, but also by the degree of enjoyment derived from using the technology. Incorporating perceived enjoyment as an antecedent to attitudes acknowledges that students' intrinsic motivations and affective reactions during technology use influence their receptiveness toward educational technologies, beyond extrinsic utilitarian assessments. This represents a crucial step toward a more holistic understanding of the drivers of student attitudes toward accepting and using technology-enabled learning. The level of perceived enjoyment experienced in using technology for education may influence the development of favorable attitudes about its use [28]. It promotes digital literacy, creativity, and critical thinking in a pleasant learning environment [5].

Learning autonomy, which is an essential antecedent to perceived behavioral control, is another modification. Learning autonomy refers to the capacity of students to direct and manage their own educational journeys, engaging in self-directed decision-making and establishing objectives [27]. Its inclusion highlights the significance of self-directed learning in influencing individuals' perceived control over their behavior. This modification recognizes that individuals who possess a higher level of learning autonomy are more likely to perceive themselves as having control over their actions and are therefore more likely to engage in the desired behavior [29]. This perception of control is expected to have a considerable influence on students' intention to adopt educational technology, such as metaverse. Autonomy empowers students to take ownership of their learning process [30]. In the metaverse, where students have access to vast amounts of information and resources, being able to independently set goals, plan their learning journey and make informed decisions becomes essential.

Additionally, student innovativeness is presented as a crucial variable that influences the perception of behavioral control. It exemplifies the capacity and motivation of students to think creatively, generate innovative ideas, and utilize technology for learning [5]. Students who are more innovative tend to have a higher perceived behavioral control when it comes to adopting technology for learning. They feel more confident and capable of using technology effectively to enhance their learning experience. Innovative students are inclined to be early adopters of innovative technologies like the metaverse. Their openness to trying new things and their ability to adapt quickly contribute to the initial success and adoption of the metaverse among students [1].

The last modification involves replacing the construct of subjective norms with social influence. This captures the impact of social influences beyond individuals' close social circles. This modification acknowledges that individuals can be influenced socially by others who are not necessarily close to them. Subjective norms in the original DTPB relates to the perceived influence or pressure that significant individuals in one's life may exert regarding the adoption of a particular technology [15,17] SN are shaped by the opinions of important others for an individual, such as peers and superiors, who influence an individual's decision-making process. Accordingly, subjective norms (peer and superior influences) and herd behavior are used as key determinants of social influence. Herd behavior pertains to the tendency of individuals to conform to the actions and behaviors of a larger group, often without critically evaluating the merits or drawbacks of the technology being adopted [31]. This behavior is driven by the desire to fit in, avoid social isolation, or gain social approval [32]. While subjective norms focus on the influence of specific individuals and their opinions, herd behavior emphasizes the impact of a collective group on an individual's decision to adopt technology [33]. Subjective norms are more personalized and tailored to an individual's social network, whereas herd behavior is characterized by a broader conformity to societal trends. By incorporating herd behavior, the influence of the various social forces and larger social groups on individuals' behavior and decision-making processes can be better understood.

3. Hypotheses development

3.1. Attitude (ATT)

Attitudes denote an individual's favorable or unfavorable emotion towards engaging in a specific behavior [13]. Individuals hold certain beliefs regarding the causal relationship between their actions. This connection aligns with the DTPB, which elucidates how an individual's attitude influences this association [17]. Similarly, it is posited that these beliefs significantly impact individuals' adoption process [34]. Various theoretical frameworks support the connection between attitude and behavioral intention. Students with positive attitudes are more inclined to adopt a new learning technology compared to those with negative attitudes. Students' intention to adopt new educational technologies is also positively influenced by positive attitudes [17,35,36].

H1. "Student attitude positively influences meta-education adoption intention.

3.1.1. Attitudinal beliefs."

The DTPB posits that attitudes are determined by perceptions of compatibility, ease of use, and usefulness. According to Davis [18], perceived usefulness (PU) refers to an individual's belief in the ability of a specific technology to enhance job performance. The decision to use or avoid the adoption of a technology is often based on the perceived impact it will have on work performance. This perception can result in either a positive or negative attitude towards its usefulness [35]. Ease of use (PEU) refers to the simplicity with which a technology can be understood and operated [18]. The perception of ease of use shapes users' attitudes towards a technology, whether positive or negative [35]. The positive impact of PU and PEU on students' attitude towards educational technologies adoption is widely established [37,38]. The likelihood of adopting metaverse-based learning is influenced by students' perception of its potential to enhance their learning endeavors. Additionally, when students find metaverse-based learning easy to use and understand, they are inclined to embrace and incorporate it into their educational activities.

Rogers [23] relates compatibility to how well a technology matches established values and past experiences. Therefore, educational compatibility reflects how well educational technology aligns with students' general expectations for learning. These expectations encompass factors such as students' current learning situation, their learning styles, and their preferred methods of engaging in learning activities [39]. Many prior studies in the field of technology adoption have found that compatibility plays a crucial role in shaping students' attitudes towards using educational technology [28,38]. Accordingly, this study suggests that students are more likely to embrace and utilize metaverse-based learning that effectively aligns with their established learning methods. Perceived enjoyment refers to the extent to which using a technology is considered enjoyable [5]. It is regarded as an inherent motivational factor for utilizing technology. According to Shen et al. [40], perceived enjoyment in the educational field plays a crucial role in bridging the gap between students' enjoyment and the effectiveness of digital learning. When students enjoy using a learning system, they are more likely to have a positive perception of it and a greater intention to use it [41,42]. The positive influence of perceived enjoyment on students' intention to embrace novel educational technology is evident [28,39,43]. Hence, students are inclined to adopt metaverse-based learning if they find it enjoyable.

H1a. "Perceived ease of use positively influences student attitude towards meta-education adoption intention".

H1b. "Perceived usefulness positively influences student attitude towards meta-education adoption intention".

H1c. "Compatibility positively influences student attitude towards meta-education adoption intention".

H1d. "Perceived enjoyment positively influences student attitude towards meta-education adoption intention".

3.2. Social influence (SI)

Ajzen [17] proposes that individuals are influenced by a complex network of subjective normative beliefs, intricately constructed based on their perception of the anticipated opinions of significant individuals in their social sphere. These opinions act as personal benchmarks that motivate individuals to embrace new behaviors in their daily activities. The favorable impact of subjective norms on students' intention to adopt technology has been consistently verified [17,39,44].

H2. "Social influence positively influences student meta-education adoption intention".

3.2.1. Social beliefs

Replacing subjective norms with a multi-dimensional construct of social influence, comprising peer influence, superior influence, and herd behavior, is a justifiable evolution in understanding how individuals are influenced by their social environment. Subjective norms, while valuable, provide a one-dimensional view of social influence by primarily focusing on perceived societal expectations. However, human behavior is far more complex and nuanced, shaped by a variety of social dynamics. Peer influence accounts for the impact of one's peers, who often play a significant role in shaping attitudes and behaviors through peer pressure, role modeling, and shared experiences. Superior influence acknowledges the impact of authority figures, mentors, or leaders, who exert considerable influence over individuals due to their expertise or status. Herd behavior acknowledges how individuals tend to follow and imitate the actions and behaviors of a larger group. It emphasizes the influence and significance of collective decision-making. These factors help in comprehending how social influence affects our lives more thoroughly. This increases our understanding and prediction of human behavior in society.

Peers and teachers impact students' use of learning technologies [27,38] When students engage in a particular behavior, the likelihood of them persisting in that approach is heightened by receiving favorable feedback from their peers, including friends and colleagues [45]. Furthermore, positive feedback from a supervisor, such as an instructor, regarding a behavior further increases the probability of an individual, specifically students, maintaining that style. Herding can be defined as the phenomenon whereby individuals choose to imitate or adopt group behaviors instead of making independent decisions based on their own confidential information [46]. Herd behavior represents the actions of individuals within a group who act without centralized direction [47]. Although several have examined herd behavior [46,48], there is a dearth of research exploring its implications for metaverse-based learning adoption.

This study introduces herd behavior as a dimension of social influence that plays a significant role in technology adoption such as metaverse-based learning. In the context of technology adoption, herd behavior can influence the rate at which innovative technologies are embraced by society [49]. When an innovative technology emerges (i.e., metaverse), individuals (i.e., students) often look to others for guidance on whether to adopt it or not. This is because people tend to seek validation and reassurance from their social networks [50,51]. If many people within their network are adopting a particular technology, it creates a sense of social proof and increases the likelihood of adoption [52].

H2a. "Peers' influence positively influences social influence".

H2b. "Superiors' influence positively influences social influence".

H2c. "Herd behavior positively influences social influence".

3.3. Perceived behavioral control (PBC)

Perceived behavioral control (PBC) denotes an individual's perceptions of the difficulty or ease related to carrying out a specific behavior [15]. Individuals hold control beliefs intertwined with their perceptions, which can either impede or facilitate the execution of a given behavior [17]. PBC plays a crucial role in influencing individuals' actions by reflecting their belief in their ability to successfully perform a specific task [15]. Here, PBC relates to students' belief in their ability to adopt a particular technology and the extent to which they perceive control over such adoption to enhance their learning experience. According to DTPB, individuals are inclined to adopt technology if they perceive themselves as having control over the behavior. Higher levels of PBC are associated with greater intention to adopt technology among students [5152]. Students' intentions to incorporate technology for educational purposes are significantly influenced by their beliefs regarding factors such as available opportunities, resources, and the overall learning environment [36,44].

H3. "Student perceived behavioral control positively influences meta-education adoption intention".

3.3.1. Control beliefs

Perceived behavioral control encompasses two facets: self-efficacy (belief in one's own ability), and resource-facilitating conditions (perceived control over resources and conditions that facilitate technology adoption). Bandura [53] provides a foundational definition of self-efficacy as the subjective evaluation individuals make regarding their own abilities and motivations when undertaking specific tasks. Hence, individuals who have a strong belief in their ability to successfully perform a specific behavior are more likely to exhibit that behavior [38]. The constructs of resource-facilitating conditions are perceived as external factors that are associated with the contextual environment in which the adoption of a particular innovation or technology is expected to occur [13]. Consequently, comprehending the anticipated impact of resource-facilitating conditions holds significant importance in the examination of human behavior within the realm of Information Systems (IS) research. Resource-facilitating conditions refer to the availability and accessibility of resources that support the adoption and use of a particular technology [28,38] In the context of student adoption intention of meta-education, resource-facilitating conditions play a crucial role in shaping students perceived behavioural control. When students perceive that they have access to the necessary resources, such as technology tools, learning materials, and support systems, they are inclined to believe that they have the capability to effectively use meta-education. This perception of control over their ability to use the technology influences their behavioural intentions to adopt and engage with meta-education.

While self-efficacy pertains to the overall assessment of one's capability to execute a task [54] learner autonomy gauges the degree to which students assume responsibility and exert authority over their learning journey using technology. Autonomy has demonstrated its pivotal role in fostering acceptance technology [71]. Even though metaverse learning offers heightened mobility and adaptability, it necessitates learners to possess intrinsic self-motivation and disciplined self-management. Personal innovativeness serves as a metric to assess the extent to which an individual possesses an inherent propensity to experiment with and embrace emerging IT solutions [55]. Individuals exhibiting prominent levels of innovativeness tend to possess a greater capacity to tolerate uncertainty and risk, displaying a heightened propensity for embracing novel ideas and embracing change [5]. As a result, it is proposed that a person's inherent innovativeness, as evidenced by a tendency toward taking risks when it comes to emerging technologies, has a significant cognitive influence on how they perceive and comprehend information technology [1]. Students who demonstrate a heightened level of personal innovativeness are more inclined to have confidence in their ability to acquire and adapt to new educational methods, thus reinforcing their perceived behavioral control.

H3a. "Student self-efficacy positively influences perceived behavioral control".

H3b. "Resource-facilitating conditions positively influences Perceived behavioral control".

H3c. "Student autonomy positively influences perceived behavioral control".

H3d. "Student innovativeness positively influences perceived behavioral control".

4. Research methodology

An online questionnaire survey was chosen as the primary method of data collection for this study. This approach was selected due to its efficiency in reaching a broad audience and its ability to capture valuable insights from higher education students with prior experience in VR technologies. The questionnaire items were adapted from well-established literature, as detailed in Appendix A. These items were rigorously selected to guarantee their relevance to the research objectives. The items incorporated in the questionnaire were meticulously selected from well-established studies within the field of educational technology, with a specific focus on contexts similar to this study, such as VR-based education and meta-education. The choice of these items was driven by their prominence in the existing literature, where they had been validated and demonstrated reliability in assessing relevant constructs. All items were measured using a 5-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree", providing a nuanced view of participants' opinions.

Data collection for this study spanned four months, from April 2023 to July 2023. The survey link was directly distributed to the intended respondents by utilizing multiple online educational platforms such as Moodle, Zoom, and Microsoft Teams. These platforms were used due to their availability to students and their popularity within the learning environments in Jordan. Prior to distribution, the questionnaire underwent a rigorous evaluation process. Three academics with extensive experience in educational technologies reviewed the questionnaire to assess the relevance and clarity of the items. Specifically, a face-to-face meeting was organized with the panel members to assess the questionnaire form. The outcomes of the meeting indicated the necessity for slight modifications to the wording of a few items, all of which were duly considered and implemented. Such feedback was used to refine the questionnaire, ensuring its quality and comprehensibility. Additionally, a pilot test was conducted with 64 students to assess the questionnaire's reliability and comprehensibility further. The results of the pilot test confirmed the internal consistency of the questionnaire. Specifically, all constructs within the questionnaire achieved a Cronbach's alpha coefficient greater than 0.7, indicating adequate reliability [56]. Hence, no modifications were made based on the pilot study.

Participant groups were carefully selected. They were higher education students with prior experience in VR technologies. These students possessed relevant insights into the integration of meta-education tools and VR technologies in higher education settings. Hence, this specific group of students was best positioned to provide valuable input on the subject matter. Accordingly, the study employed a purposive non-random sampling strategy and applied the exponential snowball sampling method [57]. In the implementation of the exponential snowball sampling method, multiple referrals were sought from previously recruited students with expertise in VR technologies, contingent upon their alignment with the specified criteria. This method, as demonstrated in this study, proved apt for evaluating populations characterized by distinctive attributes or those difficult to ascertain due to their unique nature [1]. Moreover, to ensure that all participants met the eligibility criteria, a screening question was deliberately included at the beginning of the questionnaire. The initial inquiry concerned the respondent's previous experience with VR technologies. Only those individuals who provided confirmation of their familiarity with VR technologies were permitted access to the entire survey. This phase was crucial in guaranteeing the accomplishment of the study's objectives.

The study's research methodology was rigorously implemented in accordance with ethical principles. The participants were fully informed about the research objectives, procedures, and their rights, and provided informed consent, ensuring voluntary participation. Additionally, the participants were afforded sufficient time to complete the questionnaire and were briefed on the study's confidentiality. A total of 613 questionnaires were returned. Of the 613 questionnaires distributed, 17 were returned incomplete (over 80 % of the questions in these questionnaires left unanswered) and, therefore, were excluded from the analysis. The remaining 596 questionnaires were considered valid and suitable for analysis. This sample size was considered sufficiently robust for this study. Adequacy was determined based on factors such as the specific nature of the research, and the statistical power required for meaningful analysis [58].

Based on the profile of the 596 respondents in this study, descriptive statistics reveal several key characteristics. In terms of gender distribution, 54 % (N = 322) of the respondents identified as males, while 46 % (N = 274) identified as females. Regarding the type of university attended, 63 % (N = 375) of the respondents were from public universities, while 37 % (N = 221) were from private universities. When considering age groups, 23 % (N = 137) of the respondents fell within the 18–22 years range, 44 % (N = 263) were aged between 23 and 27 years, 20 % (N = 119) were aged between 28 and 32 years, and 13 % (N = 77) were aged over 33 years. Furthermore, the educational background of the respondents showed that 81 % (N = 483) were undergraduate students, while 19 % (N = 113) were postgraduate students. By considering gender, type of university, age groups, and educational background, the

Table 1
Construct reliability and validity.

Construct	Item	Factor Loading	α	CR	AVE	VIF
Attitude	ATT_1	0.848	0.87	0.911	0.72	1.491
	ATT_2	0.851				
	ATT_3	0.846				
	ATT_4	0.849				
Student Autonomy	AUT_1	0.907	0.896	0.935	0.828	1.172
	AUT_2	0.910				
	AUT_3	0.913				
Compatibility	COM_1	0.895	0.833	0.928	0.811	1.604
	COM_2	0.907				
	COM_3	0.900				
Perceived Behavioural Control	PBC_1	0.877	0.903	0.932	0.774	1.505
	PBC_2	0.894				
	PBC_3	0.885				
	PBC_4	0.864				
Perceived Enjoyment	ENJ_1	0.883	0.869	0.92	0.792	1.492
	ENJ_2	0.887				
	ENJ_3	0.900				
Perceived Ease of Use	PEU_1	0.916	0.864	0.917	0.786	1.688
	PEU_2	0.860				
	PEU_3	0.882				
	PEU_4[a]	0.506				
Resource-Facilitating Conditions	RFC_1	0.918	0.896	0.935	0.827	1.216
	RFC_2	0.894				
	RFC_3	0.917				
Perceived Usefulness	PU_1	0.920	0.889	0.931	0.818	1.734
	PU_2	0.902				
	PU_3	0.891				
	PU_4[a]	0.623				
Herd Behaviour	HED_1	0.911	0.887	0.93	0.815	1.42
	HED_2	0.898				
	HED_3	0.899				
Student Innovativeness	SIN_1	0.900	0.903	0.939	0.837	1.219
	SIN_2	0.924				
	SIN_3	0.920				
Adoption Intention	ADI_1	0.859	0.863	0.907	0.709	–
	ADI_2	0.844				
	ADI_3	0.834				
	ADI_4	0.830				
Peer Influence	PEI_1	0.908	0.893	0.933	0.823	1.423
	PEI_2	0.917				
	PEI_3	0.898				
Student self-efficacy	SEE_1	0.902	0.883	0.928	0.811	1.227
	SEE_2	0.916				
	SEE_3	0.883				
Social Influence	SI_1	0.870	0.892	0.925	0.755	1.37
	SI_2	0.865				
	SI_3	0.876				
	SI_4	0.866				
Superior Influence	SUI_1	0.948	0.809	0.861	0.677	1.002
	SUI_2	0.755				
	SUI_3	0.750				

- α: Cronbach's alpha, CR: composite reliability, AVE: average variance extracted.
[a] Item deleted: Exhibited a factor loading <0.708.

Table 2
Discriminant validity.

	ATT	COM	HED	ADI	PEI	PBC	PEU	ENJ	PU	RFC	SI	AUT	SIN	SEE	SUI
ATT	**0.848**	0.604	0.394	0.740	0.406	0.569	0.561	0.621	0.560	0.344	0.552	0.339	0.341	0.306	0.057
COM	0.529	**0.900**	0.263	0.402	0.251	0.351	0.562	0.530	0.608	0.245	0.338	0.224	0.228	0.221	0.022
HED	0.347	0.234	**0.903**	0.513	0.609	0.403	0.267	0.240	0.197	0.341	0.657	0.311	0.317	0.361	0.040
ADI	0.642	0.351	0.449	**0.842**	0.530	0.718	0.410	0.467	0.366	0.437	0.754	0.417	0.445	0.365	0.056
PEI	0.358	0.222	0.544	0.466	**0.907**	0.391	0.304	0.236	0.255	0.316	0.656	0.225	0.343	0.214	0.035
PBC	0.505	0.313	0.361	0.634	0.351	**0.880**	0.372	0.315	0.281	0.567	0.550	0.471	0.599	0.502	0.042
PEU	0.490	0.494	0.235	0.355	0.269	0.330	**0.886**	0.567	0.636	0.263	0.278	0.237	0.292	0.183	0.048
ENJ	0.540	0.465	0.211	0.405	0.208	0.279	0.494	**0.890**	0.528	0.184	0.330	0.210	0.173	0.194	0.039
PU	0.494	0.540	0.175	0.321	0.228	0.252	0.559	0.466	**0.904**	0.209	0.257	0.194	0.223	0.130	0.028
RFC	0.304	0.219	0.304	0.385	0.283	0.511	0.234	0.162	0.187	**0.910**	0.337	0.321	0.355	0.351	0.041
SI	0.487	0.300	0.585	0.662	0.586	0.494	0.245	0.290	0.228	0.302	**0.869**	0.311	0.341	0.283	0.044
AUT	0.299	0.199	0.278	0.366	0.201	0.424	0.209	0.186	0.175	0.289	0.278	**0.910**	0.299	0.327	0.049
SIN	0.302	0.204	0.284	0.393	0.309	0.542	0.261	0.153	0.202	0.319	0.307	0.269	**0.915**	0.372	0.045
SEE	0.269	0.195	0.319	0.318	0.190	0.448	0.162	0.170	0.117	0.312	0.251	0.291	0.332	**0.900**	0.054
SUI	0.017	0.015	0.009	0.029	0.041	0.003	0.004	0.001	0.020	−0.006	0.029	−0.024	−0.028	−0.034	**0.823**

Note: The Fornell–Larcker criterion is applied below the main diagonal, whereas the HTMT is applied above the main diagonal. The main diagonal is highlighted in bold, representing the $\sqrt{\text{AVE}}$.

research better understands the different respondent pool's viewpoints. A rigorous demographic study increases the results' validity and application, providing useful insights for both academia and practical implementation in higher education settings.

5. Data analysis

The collected data were subjected to comprehensive analysis employing the Variance-based Structural Equation Modelling (SEM) method, commonly referred to as "Partial Least Squares (PLS)." PLS-SEM has gained widespread recognition and popularity within the research community due to its unique strengths, particularly its flexibility in handling varying sample sizes and distribution requirements, distinguishing it from other traditional techniques such as "covariance-based SEM (CB-SEM)" [59]. PLS-SEM was selected for analysis based on the dataset's non-normal distribution, which is typical in social science and management studies [60]. To perform this PLS-SEM analysis, the SmartPLS software (version 4) was [61]. Currently, SmartPLS stands as the most exhaustive software solution for performing PLS-SEM analyses [62]. The SmartPLS developers consistently deploy updates that expand the software's functionalities in addition to incorporating issue fixes (i.e., SmartPLS4). Furthermore, SmartPLS has been used in many research studies to effectively handle sequential mediation [63,64]. Recognizing the importance of a systematic and methodical analysis, a two-phase process (measurement model and structure model) was used [59]. The measurement model phase primarily concerned the assessment of the reliability of measurements, both at the level of individual indicators (indicator reliability) and at the level of constructs (internal consistency reliability) [65]. Furthermore, the validity evaluation centered on the convergent validity of each measure [66,67]. It also evaluated the discriminant validity of a construct in relation to other construct measures within the model. The initial step at the structural model was intended to examine the structural model for potential collinearity concerns. Once the absence of collinearity concerns had been verified, the structural model's relationships, particularly the path coefficients, were assessed for significance. The third and fourth steps evaluated the model's explanation and prediction.

5.1. Measurement model

This crucial stage was intended to establish the constructs' reliability and validity of study research model. As suggested by Hair et al. [59], this phase encompassed an exhaustive examination of the measurement model's components. The reliability of latent constructs was determined through the assessment of composite reliability (CR) and Cronbach's alpha (α). These tests ensured that the constructs' indicators were internally consistent. Concurrently, the convergent validity was scrutinized by evaluating factor loadings and average variance extracted (AVE). Then, the Fornell-Larcker criterion and Heterotrait–monotrait (HTMT) were used to assess discriminant validity and verify construct distinctiveness.

As presented in Table 1, all CR and α values exceeded 0.7, signifying strong internal consistency for all constructs. In addition, every item demonstrated factor loadings exceeding 0.708, except for PU_4 and PEU_4, which exhibited factor loadings of 0.603 and 0.578, respectively. Consequently, these items were excluded from the analysis. The Average AVE values for all constructs exceeded 0.5, providing evidence of convergent validity.

The Fornell-Larcker test assumptions were satisfied, as evidenced by the fact that the $\sqrt{AVE}$ for each construct exceeded the correlations between constructs (Table 2). Also, all HTMT values were below the 0.85 threshold, confirming discriminant validity.

5.2. Structural model

Once the measurement model was deemed reliable and valid, the second phase involved the evaluation of the structural model. Following Hair et al. [59], through path coefficient analysis and bootstrapping procedures, the direct and indirect relationships between the constructs were explained, thereby testing the theoretical framework's validity.

Table 3
Assessment of explanatory power and predictive performance.

Dependant Variable	R^2	$Q^2_{predict}$	Item	$Q^2_{predict}$	$RMSE_{-PLS}$	$RMSE_{-LM}$	$RMSE_{PLS} < RMSE_{-LM}$
Attitude (ATT)	0.428	0.416	ATT_1	0.306	0.914	0.908	No
			ATT_2	0.294	0.956	0.966	Yes
			ATT_3	0.300	0.943	0.951	Yes
			ATT_4	0.296	0.940	0.950	Yes
Adoption Intention (ADI)	0.630	0.406	ADI_1	0.299	0.857	0.872	Yes
			ADI_2	0.283	0.895	0.916	Yes
			ADI_3	0.299	0.883	0.885	Yes
			ADI_4	0.268	0.900	0.919	Yes
Perceived Behavioural Control (PBC)	0.496	0.484	PBC_1	0.353	0.948	0.969	Yes
			PBC_2	0.408	0.903	0.925	Yes
			PBC_3	0.402	0.898	0.916	Yes
			PBC_4	0.333	0.972	0.988	Yes
Social Influence (SI)	0.444	0.435	SI_1	0.347	0.934	0.943	Yes
			SI_2	0.325	1.015	1.043	Yes
			SI_3	0.336	0.965	0.980	Yes
			SI_4	0.306	0.969	0.978	Yes

Initially, multi-collinearity was checked. When two or more independent variables have a strong linear association, multi-collinearity occurs, making it difficult to isolate each variable's effect on the dependent variable [68]. Multi-collinearity may provide erroneous regression coefficient estimations. Accordingly, the Variance Inflation Factor (VIF) assessment was carried out to check for multi-collinearity. All VIF values in Table 1 were below 3, indicating minimal risk of multi-collinearity among the independent variables. The research model's explanatory power was evaluated using R^2, and its predictive relevance was assessed using Q^2. R^2 values range from 0 to 1, with higher values indicating stronger explanatory power. ATT, SI, PBC explain 63 % ($R^2 = 0.63$) of the total variance in ADI (Table 3). This result underscored the moderate effectiveness of the research model in predicting meta-education adoption intention [59]. Additionally, 42.8 % ($R^2 = 0.428$) of the variance in attitude was explained by COM, PEU, PU, and ENJ. Moreover, HED, PEI, and SUI jointly contributed to elucidating 4.44 % ($R^2 = 0.444$) of the overall variance explicated in SI. Finally, RFC, SIN, and AUT collaboratively contributed to explaining 49.6 % ($R^2 = 0.496$) of the total variance in PBC. Therefore, these results were regarded as moderate.

In terms of evaluating Q^2, the dependant variables and their indicators in the research model acquired adequate predictive power (or predictive performance), as all $Q^2_{predict}$ values (on variable and indicator level) were higher than zero (see Table 3). Furthermore, the PLS Predict was employed to further assess the predictive performance of the research model [69]. The results of comparing the "root mean squared error" (RMSE) of and PLS (partial lest square model) and LM (linear regression model) demonstrated that $RMSE_{-PLS}$ for all indicators of each dependant variable were less than their $RMSE_{-LM}$, except for ATT_1 (Table 3). These findings signified that the research model exhibited a high predictive performance.

The results of the hypotheses testing based on path coefficients (β) and their corresponding p-values and t-statistics indicated that attitude (ATT; $\beta = 0.316$, $p < 0.001$), social influence (SI; $\beta = 0.362$, $p < 0.001$), and perceived behavioral control (PBC; $\beta = 0.295$, $p < 0.001$) were significant positive predictors of adoption intention for meta-education (ADI) (Table 4). Of these, Social Influence (SI) had the strongest influence on ADI, highlighting its critical role in shaping meta-education adoption intentions. Furthermore, perceived ease of use (PEU; $\beta = 0.145$, $p < 0.01$), perceived usefulness (PU; $\beta = 0.147$, $p < 0.01$), compatibility (COM; $\beta = 0.245$, $p < 0.001$), and enjoyment (ENJ; $\beta = 0.286$, $p < 0.001$) were found to positively influence ATT. These results suggested that these factors were key enablers of ATT. Notably, ENJ had the strongest effect on meta-education adoption intention, underlining the salient role of hedonic motivation in driving meta-education adoption among students. Furthermore, the findings demonstrated that herd behavior (HER; $\beta = 0.379$, $p < 0.001$) and peer influence (PEI; $\beta = 0.380$, $p < 0.001$) had significant positive effect on SI, suggesting that both factors were key determinants of SI. Surprisingly, superior influence (SUI) was not an important social factor as its effect on SI was insignificant SI (SUI; $\beta = 0.010$, $p > 0.05$). With respect to the antecedents of perceived behavioral control (PBC), self-efficacy (SEE; $\beta = 0.191$, $p < 0.001$), resources-facilitating conditions (RFC; $\beta = 0.289$, $p < 0.001$), student autonomy (AUT; $\beta = 0.195$, $p < 0.001$), and student innovativeness (SIN; $\beta = 0.333$, $p < 0.001$) were acting as key enablers of PBC. SIN generated the strongest effect on PBC highlighting its role in shaping student PBC. With regards to evaluating the effect size (f^2), the values for the hypothesized paths ranged from medium to large [70], except for the effect of SUI on SI which exhibited a small effect size. Among the predictor constructs of ATT, ENJ generated the strongest effect (0.286) on student attitude, highlighting its significant role in developing a favorable attitude towards meta-education. Furthermore, RFC was regarded as the strongest predictor (0.289) of PBC. Both PEI and HED exerted an equal effect size on SI. Finally, SI generated the strongest effect (0.362) on ADI compared to ATT and PBC. These findings suggest that HEIs and meta-education developers should prioritize these predicting factors to garner more favorable intentions towards meta-education.

6. Discussion

The empirical findings of this investigation demonstrate that students' adoption intention of meta-education is shaped by several key factors including their attitude, social influence, and perceived behavioral control. These factors show a positive significant effect on adoption intention, indicating that hypotheses H1, H2, and H3 are supported. These outcomes align with previous studies [17,36,44]. When students have high perceived behavioral control over integrating meta-education practices, they are more likely to intend to

Table 4
Hypotheses testing.

Hypothesis	Path	β	f^2	Mean	STDEV	T Statistics	CI	P value	Assumption
H1	ATT→ADI	0.316	0.181	0.316	0.032	9.757	0.251, 0.381	0.000	Supported
H1a	PEU→ATT	0.145	0.022	0.144	0.046	3.154	0.051, 0.234	0.002	Supported
H1b	PU→ATT	0.147	0.022	0.148	0.045	3.278	0.058, 0.233	0.001	Supported
H1c	COM→ADI	0.245	0.065	0.248	0.044	5.628	0.162, 0.332	0.000	Supported
H1d	ENJ→ATT	0.286	0.096	0.285	0.045	6.308	0.195, 0.374	0.000	Supported
H2	SI→ADI	0.362	0.241	0.363	0.030	12.196	0.303, 0.419	0.000	Supported
H2a	PEI→SI	0.380	0.182	0.380	0.041	9.89	0.297, 0.459	0.000	Supported
H2b	SUI→SI	0.010	0.000	0.012	0.040	0.245	−0.069, 0.083	0.807	Not Supported
H2c	HED→SI	0.379	0.182	0.379	0.039	9.759	0.301, 0.453	0.000	Supported
H3	PBC→ADI	0.295	0.157	0.295	0.030	9.921	0.235, 0.352	0.000	Supported
H3a	SEE→PBC	0.191	0.059	0.191	0.040	4.793	0.113, 0.269	0.000	Supported
H3b	RFC→PBC	0.289	0.136	0.289	0.040	7.196	0.208, 0.367	0.000	Supported
H3c	AUT→PBC	0.195	0.065	0.196	0.039	4.990	0.117, 0.270	0.000	Supported
H3d	SIN→PBC	0.333	0.181	0.335	0.042	8.016	0.253, 0.414	0.000	Supported

STDEV: Standard Deviation, CI: Confidence intervals.

adopt these techniques. Believing they can master self-regulated learning provides confidence to supplement their education. In addition, favorable attitudes toward meta-education increase adoption intentions, as students who view meta-education as valuable and worthwhile are more motivated to prioritize it. Positive perspectives on the benefits of meta-education strengthen behavioral motivations. Additionally, social influence shapes students' normative beliefs about meta-education. Peer usage and endorsement helps to legitimize meta-education and makes it socially rewarding to adopt. Students are driven by social validation to leverage popular techniques. Hence, students who believe they can employ meta-education strategies, have good attitudes about their value, and sense social desire to comply with peer norms are more inclined to use them in their studies. Perceptions of control, personal gains, and social alignment are crucial in promoting adoption.

The results demonstrate that compatibility, perceived ease of use, usefulness, and enjoyment are key determinants of student attitude. Therefore, the hypotheses H1a, H1b, H1c, and H1d are supported. While these findings are substantiated by empirical evidence in prior research [39,43]., they contradict with others [28]. Students are more inclined to incorporate meta-education into their learning when they hold the belief that its implementation is simple. Adoption is also facilitated by functionalities that appear easy to comprehend and not excessively complicated. Students are more motivated to utilize meta-education when they perceive it as beneficial for enhancing their academic performance and learning. Compatibility with students' existing study habits and learning approaches also eases adoption. Students are more receptive to meta-education methods that complement rather than require them to entirely change their current strategies. Thus, compatibility signals an easier transition. Furthermore, students who believe adopting meta-education will make learning more enjoyable and intrinsically rewarding also exhibit higher intentions to adopt it. In fact, perceived enjoyment tapped into students' motivations for greater engagement and self-fulfillment.

The empirical results here have unveiled that peer influence and herd behavior represent pivotal precursors of social influence, whereas superior influence does not substantiate a significant impact. The results provide support for hypotheses H2a and H2c, while hypothesis H2b does not receive empirical validation. The findings of this study regarding peer and superior influences partially align with prior literature. Previous research confirms the positive effect of peer and superior influence on subjective norms [27,38,71]. However, this study indicates superior influence is not a significant social factor.

There has been little research on whether herd behavior affects student intentions to adopt metaverse-based learning. This gap in knowledge is relevant because understanding the psychological and social mechanisms behind metaverse learning adoption is crucial to its successful integration. This study signifies an initial investigation into the potential ramifications of herd mechanisms on attitudes and norms regarding participation in educational initiatives within metaverse environments. It indicates that peer influence and herd behavior are two of the most influential social factors in determining students' intents to adopt meta-education. Students are more inclined to seek information regarding the norms and hazards of unconventional study methods from their peers rather than authoritative entities.

Significantly, peer influence serves to socially validate meta-education while concurrently mitigating its perceived risk. Specifically, the practice of observing fellow students proficiently employ meta-education strategies instills observers with a sense of assurance and legitimizes such behavior, thus increasing the propensity of the observers to adopt the strategies themselves. Beyond direct peer influence, students are also swayed by broader herd behavior, or the tendency to "follow the crowd". Their observation of collective peer norms and momentum shapes perceived social risks of deviating from conventional education methods. Some students may be hesitant to try meta-learning techniques before their peers, but as these methods become more popular and socially validated, they tend to attract students due to their natural desire to fit in with the crowd and follow its behaviors. Consequently, students adopt these novel and efficient learning strategies driven by their inherent tendency towards conformity.

Although it is often assumed that students are primarily influenced by directions and encouragement from authority figures such as instructors or administrators, this study indicates that peer influence and herd behavior have a greater impact on students' adoption of new instructional practices. When considering meta-education, students are more influenced by peers than authority figures. Even if teachers or principals strongly advocate meta-learning practices, students may resist owing to a lack of peer validation or fears about standing out. They tend to rely more on observing what fellow students are saying and doing, rather than on top-down recommendations from superiors. This herd mentality and stronger weighting of peer influence means students are less motivated by superior influence compared to social proof and risks of deviating from the norm set by their cohort. Consequently, the adoption of meta-education may be marginally influenced by superior influence alone. Peer influence and herd behavior, on the other hand, establish crucial social perceptions, motivations, and risk assessments that shape students' intentions.

Student self-efficacy, resource-facilitating conditions, student autonomy, and student innovativeness have been shown to positively influence students' perceived behavioral control. Such outcomes designate that hypotheses H3a, H3b, H3c, and H3d are supported. While the findings related to the positive effect of resource-facilitating conditions and self-efficacy are supported by previous research [28], the positive effect of student autonomy is also reported in the literature [27]. However, investigating student innovativeness as key control belief is less explored in the extant literature. High self-efficacy (or belief in one's own abilities), further enables students to feel empowered to leverage meta-education and self-regulated learning skills. Those who feel more assured in their capacity to take control of their education are more likely to adopt supplemental techniques that require self-direction. In addition, when students have adequate resource-facilitating conditions, such as support from teachers, peers, or technology to enable meta-learning, they also demonstrate higher intentions to adopt meta-education. Access to needed resources gives students the means to feel meta-education is within reach.

Students are more inclined to explore innovative approaches, such as meta-education, when they perceive a sense of autonomy in their learning. Therefore, independent learners find the reflective and cognitive methods of meta-education to be compelling. The study reveals student innovativeness contributes in increasing meta-education adoption intention. Metacognitive self-regulation and innovative activities are common among open-minded students. Their innovativeness gives them confidence to use meta-education's cognitive and introspective methods.

7. Research implications

7.1. Theoretical implications

This study investigating meta-education adoption intention among higher education students carries significant theoretical implications, bridging a notable gap in the existing research landscape. The scarcity of prior research dedicated to the exploration of meta-education adoption intention is noteworthy. By delving into this uncharted territory, the study lays the groundwork for a more comprehensive understanding of how students perceive and engage with meta-education. While some studies have ventured into this domain, they rely on established models such as the TAM and UTAUT models. Although existing models contribute positively to understanding meta-education adoption, they lack comprehensiveness in incorporating crucial belief aspects such as attitudes, hedonic motivation, and individual personality traits that significantly influence people's decision-making during adoption.

This research provides significant value by applying an extended version of the DTPB) model to investigate the adoption of meta-education. The inclusion of extra factors into the DTPB marks a theoretical progression, allowing for a more nuanced examination of the various influences on students' intentions to adopt meta-education. Specifically, incorporating dimensions such as student autonomy, innovativeness, enjoyment, and herd behavior provides a more comprehensive, ecologically valid perspective on drivers of meta-education adoption compared to prior models. By elucidating this broader range of factors influencing students' meta-education engagement intentions, this research significantly enhances theoretical perspectives. The proposed expanded DTPB model constitutes an important evolution in conceptualizing meta-education adoption decision-making. This multidimensional framework serves as a useful theoretical tool for researchers, educators, and policymakers seeking deeper insight into students' meta-education choices. Overall, the enriched DTPB lens enables more nuanced, holistic examination of meta-education adoption intention drivers, making a substantial theoretical contribution.

The results of this study provide robust empirical support for the efficacy of the proposed extended DTPB framework in elucidating the complex drivers of meta-education adoption intentions among higher education students. The model exhibited substantial explanatory power, accounting for 70 % of the variance in students' intentions to engage in meta-educational practices. This underscores the utility and relevance of applying the DTPB model to understand meta-education adoption in an educational context. It also highlights the value of incorporating multiple factors, including individual characteristics and attitudinal orientations, to gain a nuanced understanding of students' motivations regarding meta-education uptake. Overall, this research makes important theoretical contributions to the emergent literature on meta-education by demonstrating the advantages of a comprehensive framework that considers autonomous motivations, innovation tendencies, affective factors like enjoyment, and social influences in shaping students' decision-making. The robust predictive capacity of the extended DTPB model underscores the significance of acknowledging the multifaceted drivers that govern students' intentions to adopt meta-educational approaches. These insights help to establish a stronger theoretical foundation to guide further scholarly inquiry into this evolving domain.

7.2. Practical implications

Beyond its theoretical contributions, this study holds significant implications for the ongoing transformation of education. By shedding light on the factors influencing meta-education adoption, it equips educational institutions with insights into how to foster a more pro-active and innovative learning environment. The positive impact of perceived ease of use, perceived usefulness, perceived enjoyment, and compatibility on student attitude toward meta-education adoption intention has several practical implications for educational institutions, platform developers, and policymakers. Educational platforms should prioritize user-centered design principles to enhance perceived ease of use. This involves creating intuitive interfaces, providing clear instructions, and offering user-friendly features. Students are more inclined to use meta-education platforms that are easy to use. Additionally, instructors and platform developers must communicate meta-education tool usefulness. Highlighting how these tools can improve learning, save time, or offer unique benefits will boost student adoption intentions. In the same vein, meta-education platforms should collect user feedback and suggestions. Addressing user problems and improving based on feedback can boost perceived usefulness and adoption intentions. Educational institutions should train and support professors and students in meta-education tool utilization. This increases perceived ease of use and enjoyment, improving adoption rates.

It is essential to make sure that meta-education resources are compatible with the existing learning management systems (LMS), or educational platforms used by the institution. This compatibility streamlines access and reduces the learning curve for students. Similarly, ensuring that meta-education resources are accessible across a variety of devices (e.g., computers, tablets, smartphones) is necessary. This compatibility allows students to engage with meta-education content at their convenience, whether on campus or off-campus. Moreover, it is important to align meta-education with the existing curriculum to make it compatible with students' academic goals. When students perceive that meta-education complements their primary coursework, they are more likely to adopt it willingly. Incorporating elements of perceived enjoyment, such as gamification, interactive content, and engaging activities, can make meta-education more enjoyable for students. When learning is fun and enjoyable, students are more likely to adopt and continue using the platform.

Students recognize peer influence and herd behavior as the main determinants of social influence regarding meta-education adoption intention. Hence, educational institutions should encourage the formation of study groups and peer networks where students can discuss and share their experiences with meta-education. Positive peer influence can help spread awareness about the benefits of meta-education. Moreover, it is deemed beneficial to incorporate peer-based learning activities within the curriculum. Collaborative projects and peer evaluations encourage students to value and apply meta-education skills, as they realize their peers are doing the same. Equally, the establishment of peer mentoring programs where experienced students help newcomers understand the importance of meta-education is crucial. These mentors can serve as role models and influencers in promoting effective learning strategies. To maximize the positive effect of herd, it is fundamental to leverage social media platforms to create communities or groups focused on meta-education. Sharing success stories, study tips, and resources can create a heard behavior effect, inspiring more students to adopt these practices. Likewise, highlighting success stories of students who have benefited from meta-education in various promotional materials and campus events would be advantageous. These stories serve as powerful testimonials and create a herd effect.

The positive effects of student innovativeness, autonomy, self-efficacy, and resource availability on students' perceived control over adopting meta-education have important practical implications. It is important for educational institutions to promote cultures of innovation and self-efficacy. Faculty should design curricula and teaching approaches that motivate students to take charge of their learning. This could involve project-based learning, self-paced modules, and opportunities for independent study. Incorporating innovative technologies and approaches into the curriculum can also be beneficial. Students should be encouraged to experiment with new tools and ideas to build curiosity and creativity. Mentorship programs where instructors help students develop self-efficacy and meta-education skills are also valuable. These support students in gaining confidence in their ability to learn independently. Finally, educational institutions are required to furnish students with a comprehensive array of both online and offline learning materials, encompassing digital libraries, instructional resources, and self-study apps. Promoting creativity and autonomy necessitates investments in contemporary classrooms and technology. Additionally, faculty members should undergo training to cultivate student independence and inventiveness. This training can be facilitated through exposure to innovative educational materials and the adoption of progressive teaching approaches as part of ongoing professional development.

8. Conclusion, limitations, and future work

This study fills an important gap in the literature by examining higher education students' intentions to adopt the emerging technology of meta-education. Since there has been little research in this new area, the extended DTPB model of this study provides valuable insights into key factors impacting students' intention to meta-education. As the proposed model predicts, attitude, social influence, and perceived control are confirmed as main drivers of adoption intention. Furthermore, the new variables of perceived enjoyment, herd behavior, student autonomy, and innovativeness help to explain these key determinants.

In particular, within attitude, compatibility, perceived ease of use, usefulness, and enjoyment are salient beliefs shaping adoption intent. For social influence, peer influence and herd behavior effects are pivotal. Significant drivers of perceived behavioral control are student autonomy, student innovativeness, resource-facilitating conditions, and student self-efficacy. These findings offer several practical implications for policymakers and educators aiming to proactively encourage meta-education adoption. Specifically, promoting positive attitudes and strengthening perceptions of behavioral control while leveraging social influences should be priorities. Moreover, initiatives that enhance salient beliefs determining attitude, social influence, and perceived behavioral could positively develop these key drivers.

While this study has made important contributions, future research could address some limitations. The model needs to be validated across diverse cultures, not just among Jordanian students. Testing the model in various cultural contexts could improve generalizability. Noting the geographic limitations of the sample can help strengthen external validity and educational technology research. Longitudinal studies could better evaluate factors predicting actual adoption over time. Tracking participants' attitudes and behaviors longitudinally could provide insights into meta-education. This has the potential to broaden causal inference and provide insights for strategic decision-making.

Examining differences across demographics such as gender and socioeconomic status may provide new insights. Studying how gender affects students' intentions to adopt meta-education could reveal patterns. Comparing attitudes, preferences, and perceived barriers between male and female students could inform gender-specific strategies to encourage acceptance. In addition, looking at how economic factors influence availability and acceptability is important. Identifying gaps in technology access and support by socioeconomic background can promote inclusive policies. As technology and education change over time, continuously measuring adoption drivers will be critical. In summary, by expanding adoption theory and offering practical implications, this study makes a significant contribution to this emerging topic. Additional research can build on these findings to improve understanding of meta-education adoption.

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The authors report there are no competing interests to declare.

Ethics declarations

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No data availability. The data that has been used is confidential, and the authors do not have permission to share it.

CRediT authorship contribution statement

Ahmad Samed Al-Adwan: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Malek Alsoud:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Na Li:** Writing – review & editing, Visualization, Validation. **Tha'er Majali:** Writing – review & editing, Visualization. **Jo Smedley:** Writing – review & editing, Visualization, Validation. **Akhmad Habibi:** Writing – review & editing, Visualization, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

The screening question: "Have you personally experienced or used Virtual Reality (VR) technologies in the past?"

- Yes
- No

Student Innovativeness [1]
SIN_1: "If I heard about a new information technology, I would look for ways to experiment with it".
SIN_2: "Among my peers, I am usually the first to try out new information technologies".
SIN_3: "In general, I am hesitant to try out new information technologies." (Reverse question)
SIN_4: "I like to experiment with new information technologies".
Student Autonomy [72]
AUT_1: "I am self-directed when it comes to study".
AUT_2: "In my studies, I set goals and have a high degree of initiative".
AUT_3: "I am able to manage my study time effectively and easily complete assignments on time".
Superior Influence [73]
SUI_1: "My university will promote the use of meta-education".
SUI_2: "Faculty and administrators at my university influence my decision to adopt meta-education".
SUI_3: "My university will provide meta-education platforms and tools makes me more likely to use them".
Peers Influence [73]
PEI_1: "My friends think I should use meta-education".
PEI_2: "My peers influence my decision to use meta-education".
PEI_3: "Seeing other students use meta-education makes me more likely to use it".
Compatibility [17]
COM_1: "Meta-education fits well with the way I like to learn my lessons".
COM_2: "Meta-education is compatible with my learning style".
COM_3: "Using meta-education fits into my specialty curriculum".
Social Influence [19]
SI1: "People who are important to me think I should use meta-education".
SI2: "People who influence my behavior think that I should use meta-education".
SI3: "People whose opinions I value prefer that I use meta-education".
SI4: "In general, the university will support the use of meta-education".

Student Self-efficacy [1]
SEE_1: "I am confident that I can perform effectively on many different tasks".
SEE_2: "When facing difficult tasks, I am certain that I will accomplish them".
SEE_3: "I believe I can succeed at most any endeavor to which I set my mind".
Perceived enjoyment [12]
ENJ_1: "Using a meta-education platform in learning will be fun".
ENJ_2: "Using a meta-education platform in learning will be enjoyable".
ENJ_3: "Using a meta-education platform in learning will be very entertaining".
ENJ_4: "Metaverse devices will make my leisure time more fun".
Superior Influence [73]
SUI_1: "My University will promote the use of meta-education".
SUI_2: "Faculty and administrators at my university influence my decision to adopt meta-education".
SUI_3: "My University will provide meta-education platforms and tools makes me more likely to use them".
Perceived Ease of Use [74]
PEU_1: "Learning to use/operate a meta-education platform would be easy to me".
PEU_2: "It is easy for me to become skillful at using a meta-education platform".
PEU_3: "I find that the use of a meta-education platform is not complicated/does not require a lot of mental effort".
PEU_4: "My interaction with meta-education platform is clear and understandable".
Attitude [75].
ATT_1 "Meta-education is an idea I like".
ATT_2: "I am positive toward meta-education".
ATT_3: "Studying through meta-education is a good idea".
ATT_4: "All things considered, my using the meta-education is beneficial".
Perceived Usefulness [1,12]
PU_1: "Meta-education platforms would enable me to accomplish tasks more quickly".
PU_2: "Using a meta-education platform would enhance my learning effectiveness "
PU_3: "Meta-education platforms would enhance the quality of my learning".
PU_4: "Meta-education platforms would be useful for my learning".
Social Influence [19].
SI1: "People who are important to me think I should use meta-education".
SI2: "People who influence my behavior think that I should use meta-education".
SI3: "People whose opinions I value prefer that I use meta-education".
SI4: "In general, the university will support the use of meta-education".
Adoption intention [74,75]
ADI_1: "Intend to use meta-education for my studies in the future".
ADI_2: "I intend to use meta-education for activities that involve learning".
ADI_3: "I intend to completely switch over to meta-education".
ADI_4: "I plan to use meta-education platform frequently".
Perceived Behavioral Control [75]
PBC_1: "I would be able to use meta-education without help".
PBC_2: "Using meta-education would be entirely within my control".
PBC_3: "I have the resources to use meta-education".
PBC_4: "I have the knowledge to use meta-education".
Recourse-facilitating Conditions [19]
RFC_1: "It is important to have the resources necessary to use meta-education".
RFC_2: "It is important that meta-education provide convenient feedback channels for problems".
RFC_3: "It is important that technicians and teachers deal with meta-education technical problems as soon as possible".
Social Influence [19]
SI1: "People who are important to me think I should use meta-education".
SI2: "People who influence my behavior think that I should use meta-education".
SI3: "People whose opinions I value prefer that I use meta-education".
SI4: "In general, the university will support the use of meta-education".
Herd Behavior [76,77]
HER_1: "My decision to engage in meta-education is influenced by the number of students who participate in it".
HER_2: "If I find that many of my colleagues are actively involved in meta-educational activities, then I would be more willing to explore these educational practices as well".
HER_3: "The more students who engage in meta-education, the more preferable it is for me to consider participating in it as well".
HER_4: "It is wise to take into account the choices and experiences of other students when deciding whether to embrace meta-educational practices".

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