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Understanding Students' Adoption of Microlearning: A TAM-PVM Integration

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ABSTRACT

Microlearning has gained significant traction in educational settings owing to its distinct pedagogical advantages. However, students' intention to use these courses remains low. To enhance students' willingness to engage with microlearning, a comprehensive framework is introduced to explore the determinants of their use intention. Data was collected via an online survey, with 320 valid responses obtained. The reliability and validity of the measurements were assessed, and hypotheses were tested using structural equation modeling analysis in *SmartPLS 3.0*. The results indicate that benefit factors including perceived usefulness and social influence are positively associated with students' perceived value, which in turn influences their subsequent intention to use microlearning. In addition, the cost factor of perceived ease-of-use positively impacts both perceived value and use intention, whereas the effect of perceived cost is insignificant. Furthermore, students' perceived value significantly predicts their intention to use microlearning. This study offers vital theoretical insights by integrating the Technology Acceptance Model and Perceived Value Model, and provides practical implications for fostering students' intention to adopt microlearning.

Keywords: Microlearning, e-Learning, Online learning intention, Student learning, Technology acceptance model (TAM), Perceived value, Social influence

1. INTRODUCTION

The emergence of microlearning marks a significant innovation in educational delivery (Alias & Razak, 2025), providing succinct and targeted learning experiences that seamlessly integrate into the busy schedules of contemporary learners. Focusing on skill-based training and education, microlearning offers brief yet effective lessons suitable for enhancing informal training performance and teaching complex material in manageable segments. Microlearning consists of compact, focused learning units that encompass condensed learning activities that are accessible across various devices such as tablets, smartphones, desktops, and laptops (Alias & Razak, 2025; Shail, 2019). These digital modules are designed to address specific learning objectives within a short timeframe, typically ranging from a few minutes to 30 minutes (Liu, 2020; Lv et al., 2020). Their adaptable format and easily digestible content underscore their versatility and appeal (Alias & Razak, 2025; Liu, 2020). The essence of microlearning lies in its conciseness, accessibility, and focused content, which together have enabled it to overcome geographical and logistical barriers, thereby transforming knowledge dissemination (Alias & Razak, 2025; Lv et al., 2020). This distinguishes it from more extensive and generalized traditional courses (Alias & Razak, 2025).

The widespread adoption and rapid proliferation of microlearning stem from its inherent alignment with the fast-paced and on-demand characteristics of the digital age (Alias & Razak, 2025). Accordingly, it is successfully integrated into a diverse array of academic disciplines including programming (ALshammari, 2024; Wu & Chen, 2015), English learning (Xu, 2018), healthcare training (Zarshenas et al., 2022), and civil engineering (Zhang, 2017). Furthermore, it has been proven effective in fostering soft skills development (Luo & Li, 2025) and enhancing creativity in complexity (Romero-Rodríguez et al., 2023) among university students. Empirical studies have consistently emphasized the positive impact of microlearning, showcasing its capacity to refine teaching methods (Díaz Redondo et al., 2021; Xu, 2018) and improve the efficiency of educational interventions (Fidan, 2023; Haghighat et al., 2023; Lv et al., 2020; Wu & Chen, 2015; Zhang, 2017). This transformative potential of microlearning in education has garnered considerable scholarly interest.

However, despite educators' widespread adoption of microlearning (Lv et al., 2020), the level of students' utilization and their intention to use such resources is not as high as expected (Gkrimpizi et al., 2023; Wang, 2019). Here, students' active engagement ultimately determines the success of microlearning. Consequently, it is important to investigate the factors influencing students' intention to use microlearning (Yin & Yu, 2014). This study aims to fill this void by identifying the key drivers that influence students' use intention. Departing from previous research that relied solely on the Technology Acceptance Model (TAM) or Perceived Value Model (PVM), this study attempts to synthesize the strengths of both frameworks, thereby facilitating a more comprehensive understanding of students' inclination to engage with microlearning.

2. LITERATURE REVIEW

2.1 Adoption of Microlearning

In the academic discourse on microlearning, the user base includes both teachers and students, necessitating a bifurcated examination of usage patterns from these distinct perspectives. We focus on the student perspective in the literature. Note that here "students" refers to learners in a broad sense. The term is not limited to those in traditional student roles but encompasses anyone engaged in the learning process. The extant literature has primarily investigated the factors shaping the adoption and utilization of microlearning. For example, Conde-Caballero et al. (2024) used TAM to examine students' acceptance of microlearning through *TikTok* in higher education. Wang (2019) noted that despite the adoption of microlearning, students' intention to engage with it remains relatively low. Moreover, students' intention to use microlearning is influenced by their perceptions of usefulness, ease-of-use, associated risks, and interactivity. Corroborating these findings, Xu and Deng (2019) emphasized the positive influence of performance expectations, effort expectations, community influence, convenience, and willingness to use on students' acceptance and utilization of microlearning. Yin and Yu (2014) examined the influence of learning motivation, experience, self-efficacy, teacher behavior, family support, and resource quality on students' adoption of microlearning, and investigated the mediating effects of perceived ease-of-use, usefulness, and enjoyment. Finally, Salas-Díaz and González-Bello (2023) focused on the effects of technological affinity, motivation to learn, and perceived usefulness.

However, despite the widespread adoption of microlearning in educational settings (Lv et al., 2020), the depth and implications of student engagement with these resources remain unclear. Empirical studies on the mechanisms that govern students' use of microlearning and the factors influencing their engagement are lacking (Yin & Yu, 2014). Given that the effectiveness of microlearning is ultimately dependent on student participation, their usage patterns and preferences must be examined (Yin & Yu, 2014). Thus, this study endeavors to fill this gap by employing empirical research methodologies to explore students' use of microlearning and unravel the underlying mechanisms that influence their utilization. To systematically decode these patterns, we grounded our investigation in established technology adoption frameworks, beginning with TAM.

2.2 Technology Acceptance Model

TAM, introduced by Davis (1989), provides a framework for understanding the factors that influence the acceptance of new technologies. The model posits that an individual's decision to adopt a technology is driven by their intention to use it, which in turn is influenced by their attitude toward its use. This attitude is then shaped by their perceptions of the usefulness and ease-of-use of technology, which are both influenced by external variables such as system characteristics, social influence, and facilitating conditions. The predictive power of TAM is verified in various contexts including mobile shopping (Zhang & Mao, 2008), virtual reality (Manis & Choi, 2019; Nilashi & Abumalloh, 2025), health applications (Park et al., 2025a; Wang et al., 2025), and artificial intelligence-based intelligent products (Almeida et al., 2025; Sohn & Kwon, 2020). This demonstrates its efficacy in explaining users' adoption of emerging technologies.

Microlearning, a novel online educational approach, is also amenable to analysis through a TAM lens when delivered via digital platforms or tools. Several studies have leveraged this model to explore microlearning adoption. For example, Wang (2019) identified perceived usefulness and perceived ease-of-use as pivotal factors influencing adoption decisions. Isibika et al. (2023) revealed that perceived ease-of-use played a more significant role in microlearning acceptance than perceived usefulness. Further expanding this framework, Yin and Yu (2014) identified external variables that affect these perceptions, such as students' learning motivation, learning experience and self-efficacy, teacher behavior, family support, and resource quality. Furthermore, Xu and Deng (2019) combined TAM with the unified theory of acceptance and use of technology (UTAUT) to develop a model tailored to higher vocational college students' acceptance and use of library information literacy via microlearning, emphasizing the direct effects of perceived usefulness and ease-of-use on user intention. However, their study did not explore the underlying mechanisms, particularly the mediating role of user attitude as posited by TAM.

Despite the widespread acceptance and validation of TAM, criticisms have emerged, particularly regarding its overemphasis on attitude toward technology. Scholars contend that perceived value, which encompasses both the benefits and costs associated with technology use, may be a more comprehensive predictor of adoption than attitude alone (Zeithaml, 1988; Zhang & Mao, 2008). In the domain of m-commerce, perceived value has been shown to exert a more profound influence on behavioral intentions than attitude toward technology (Kim et al., 2007; Kleijnen et al., 2007). Given these considerations, our study endeavors to bridge this gap by integrating TAM with PVM. This approach aims to provide a nuanced understanding of the factors influencing students' microlearning use intention and to uncover the mechanisms underlying these effects.

2.3 Perceived Value Model

The concept of perceived value is intricately linked to consumers' holistic assessment of a product's worth, which is grounded in a comparative analysis of the benefits derived versus the costs incurred (Zeithaml, 1988). Here, PVM provides a refined perspective on the motivations underlying technology adoption and utilization. The model goes beyond the utilitarian focus of TAM by acknowledging the multifaceted nature of value, recognizing that users consider not only the functionality and usability of technology, but also the personal gratification, social prestige, and enjoyment it may offer (Zhang & Mao, 2008). Furthermore, PVM surpasses TAM by considering the costs associated with technology adoption. Research has verified that financial considerations significantly impact the intention to adopt technology, as mediated by perceived value (Kim et al., 2007). Moreover, PVM enhances the explanatory power of TAM. Research highlights consumers' perception of value as a more critical determinant of their actual behavioral intentions than their attitudes toward the mere utilization of technology in the mobile-commerce domain (Kim et al., 2007; Kleijnen et al., 2007).

Therefore, this study aims to amalgamate the strengths of both PVM and TAM to explore students' intentions to use microlearning. By integrating the exhaustive value assessment framework of PVM with well-established TAM predictors, we aim to develop a more nuanced and comprehensive understanding of microlearning adoption.

3. CONCEPTUAL FOUNDATION AND HYPOTHESIS DEVELOPMENT

Drawing on the aforementioned literature, we now proceed to delineate our research model based on TAM and PVM. Before delving into hypothesis development, we first articulate the broader research questions that set the stage for the theoretical contribution of the study. The research questions focus on exploring the new perspective integrating TAM and PVM offers. Specifically, we address the following two questions: (1) *How does integrating TAM and PVM enrich the understanding and application of these two theories?* (2) *How does this new integrated perspective contribute to the existing knowledge of technology adoption behavior?*

We integrate the original TAM with the PVM for two reasons. First, our research aims to highlight the unique contribution of perceived value in PVM in understanding students' microlearning adoption. This core focus may be muddied by the numerous incorporated factors in TAM and UTAUT. Thus, starting with the fundamental TAM enables a clear demonstration of the new insights from integrating PVM, particularly the in-depth cost-benefit value-based analysis. Second, our TAM-PVM integration offers distinct explanatory power. By reclassifying the TAM variables into a cost-benefit structure and emphasizing perceived value as a central mediator, we provide a more nuanced view of students' adoption decision-making in the microlearning context. This approach is tailored to the specific cost-benefit trade-offs in microlearning adoption, which may differ from those in TAM or UTAUT scenarios.

Integrating TAM and PVM is anchored in their complementary roles in explaining technology adoption behavior. TAM provides a functional perspective by identifying the key drivers of adoption—perceived usefulness and perceived ease-of-use—which align with the benefit and effort-based cost dimensions of technology evaluation (Davis, 1989). Conversely, PVM extends this framework by conceptualizing adoption as a value-maximization process in which users holistically weigh both monetary and non-monetary costs and multidimensional benefits (Zeithaml, 1988).

To bridge these theories, we reclassify the core variables of TAM into a dual cost-benefit structure. *Benefit factors* include perceived usefulness (functional utility) and social influence (social utility), the latter reflecting conformity-driven social identity gains (Venkatesh et al., 2003). *Cost factors* encompass perceived ease-of-use (non-monetary effort costs) and perceived cost (perceived monetary cost), the latter explicitly introduced through PVM to address the limited consideration of financial barriers in TAM.

Crucially, perceived value—PVM's central mediator—operates as the mechanism that synthesizes these benefits and costs into a net appraisal. This mediation step extends the TAM framework by replacing the traditional attitude-mediated pathway (Davis, 1989) with a value-driven cognitive calculus—consistent with empirical precedents where attitude is omitted without compromising predictive validity (Bonilla, 2011; Or, 2024). Specifically, students first assess whether the aggregated benefits (perceived usefulness + social influence) sufficiently offset the combined costs (perceived ease-of-use + perceived cost), forming behavioral intentions directly through net perceived value rather than through attitude. This integration clarifies the decision mechanism: the functional variables of TAM define inputs to the value calculus of PVM, while PVM explains how these inputs are cognitively processed into behavioral outcomes. This aligns with Zeithaml's (1988) theory and contemporary TAM applications that bypass attitude mediation (Bonilla, 2011).

To enhance the theoretical clarity of our model, we provide a comparative summary table (Table 1) and briefly discuss how this model deviates from prior TAM-PVT hybrid models in terms of structure, construct selection, and context application. Notably, our model is distinct because it (1) explicitly frames antecedents into a dual cost-benefit structure, (2) positions perceived value as the sole mediator, and (3) focuses on microlearning adoption, a context under-examined in prior hybrid models. Its fundamental mechanism also holds significant potential for generalization beyond microlearning to other digital learning environments such as MOOCs (Massive Open Online Courses), learning management systems (LMS), educational apps, and virtual/augmented reality, provided context-specific salient factors are mapped into the benefit and cost aggregates while maintaining the core structural relationships.

Core Structural Features (Antecedents → Mediator(s) → Outcome)	Mechanism	Context	Source
Gamification → Perceived Value → Behavioral Intention; Perceived Usefulness, Perceived Ease-of-Use → Attitude → Behavioral Intention	Perceived Value mediates gamification effect; Attitude mediates Perceived Usefulness/Perceived Ease-of-Use effect	Digital Banking Service	(Viet Tam et al., 2024)
Perceived Value, Knowledge Sharing, Perceived Usefulness, Perceived Ease-of-Use, Perceived Privacy Awareness, Perceived Security → Behavioral Intention	Perceived Value as direct antecedent alongside others; No mediation	Mobile Wallet	(Salah & Ayyash, 2025)
Perceived Price Value, Knowledge Sharing, Perceived Usefulness, Perceived Ease-of-Use, Perceived Enjoyment → Behavioral Intention Perceived Ease-of-Use → Perceived Usefulness → Behavioral Intention	Perceived Price Value as direct antecedent alongside others	Tourist Mobile Hotel Booking	(Mohamad et al., 2021)
Benefit (Perceived Enjoyment, Convenience, Perceived Ease-of-Use, Perceived Usefulness); Sacrifice (Perceived Risk, Repulsion, Security Concern) → Perceived Value & Attitude → Behavioral Intention	Perceived Value and Attitude as parallel mediators between benefit/sacrifice clusters and Behavioral Intention	Mobile Payment Platforms	(Park et al., 2025b)
Confirmation → Perceived Ease-of-Use, Perceived Usefulness → Satisfaction → Perceived Value, Self-Efficacy → Behavioral Intention	Perceived Value, Self-Efficacy, Satisfaction as parallel mediators between antecedents and Behavioral Intention	On-demand Ride Services	(Malik & Rao, 2019)
Perceived Value, Compatibility, Perceived Enjoyment, Social Influence → Trust, Satisfaction → Behavioral Intention	Perceived Value as a direct antecedent; Trust and Satisfaction mediate Behavioral Intention	Tourists' Use of Mobile Wallets	(Gupta et al., 2023)
Benefit (Perceived Usefulness, Social Influence); Cost (Perceived Ease-of-Use, Perceived Cost) → Perceived Value → Behavioral Intention	Perceived Value as the sole mediator synthesizing aggregated benefits and costs	Microlearning Adoption (Students)	This study

Table 1. Comparison of TAM-PVT Hybrid Models

In the subsequent sections, we elaborate on the conceptualization of each variable and its respective influence to lay the groundwork for the development of our hypotheses and research model.

3.1 Effects of Benefit Factors

3.1.1 Effect of Perceived Usefulness on Perceived Value. Perceived usefulness refers to the degree to which individuals anticipate that adopting a new technology will enhance their work performance (Lee, 2006). In the microlearning context, this concept is translated into users' belief in the capability of a microlearning system to increase their knowledge and facilitate the achievement of learning goals (Liao et al., 2022). Based on TAM, perceived usefulness is defined as an extrinsic motivation metric (Cheung & Vogel, 2013), reflecting users' assessment of the technology's attractiveness and practical worth in improving their actions (Kim et al., 2007). This construct bridges external stimuli and the likelihood of engagement, highlighting the interaction between incentives and user behavior.

Microlearning, characterized by focused themes and streamlined knowledge delivery (Lv et al., 2020), offers students a more efficient and effective learning experience. This increased efficiency, in turn, promotes students' greater perceived value of microlearning. Given this connection, we propose a positive relationship between students' perceived usefulness of microlearning and their subsequent perceived value of the educational approach.

Hence, we formulate the following hypothesis: *H1a: Perceived usefulness positively affects students' perceived value of microlearning.*

3.1.2 Effect of Perceived Usefulness on Use Intention. Perceived usefulness serves as a cornerstone of TAM. Its pivotal role in promoting the adoption of information technology is well documented in numerous studies (cf. Davis, 1989; Kim et al., 2007; Venkatesh & Davis, 2000). Extensive empirical evidence highlights the predictive power of perceived usefulness in shaping user intentions to adopt diverse technologies, ranging from smartphones (Park & Chen, 2007) to personal digital assistants (Teng & Lu, 2010) and new electronic authentication services (Kim & Kyung, 2023).

In the education domain, perceived usefulness emerges as a significantly positive factor influencing students' willingness to adopt e-learning systems (Jaiyeoba & Iloanya, 2019; Lee, 2006; Salimon et al., 2023). Notably, it also considerably affects students' decisions to maintain their use of microlearning (Wang et al., 2021), highlighting its importance not only in the initial adoption, but also in the continuous use of educational technologies.

Given this substantial evidence, we propose the following hypothesis: *H1b: Perceived usefulness positively affects students' microlearning use intention.*

3.1.3 Effect of Social Influence on Perceived Value. Social influence is conceptualized as individuals' perception that important others think they should adopt a particular technology during the acceptance process (Venkatesh et al., 2003). In the microlearning context, this concept translates into students' awareness of the expectations that key figures in their social circles impose on them, including friends, classmates, and teachers, who advocate for the use of the educational approach. Similar to the marketing domain, where the opinions of influencers (Burt, 1999) and online reviews (Elwalda & Lu, 2016) significantly shape consumers' perceived value of a product, social influence in educational settings molds the perceived value of online learning communities (Zhang et al., 2019).

Students' learning environments are inherently social, with classmates and teachers playing crucial roles. The tendency to conform to the behaviors and preferences of one's peers and mentors, often driven by the desire to gain social identity and acceptance, is well documented. In this regard, when individuals in a student's immediate social environment support the adoption of microlearning as a valuable learning resource, it is reasonable to assume that this endorsement will positively affect the student's perceived value of the educational approach.

Hence, we formulate the following hypothesis: *H2a: Social influence positively affects students' perceived value of microlearning.*

3.1.4 Effect of Social Influence on Use Intention. Social influence, a multifaceted construct, influences human behavior through intricate cognitive pathways and social construction (Calder & Burnkrant, 1977).

According to Social Identity Theory, individuals inherently categorize themselves into distinct social groups to affiliate and identify with others who share common values and practices (Tajfel & Turner, 2004). In online communities, such as those focusing on environmental issues, participants develop a shared sense of purpose and identity, fostering a collective mindset among them.

In the domain of information systems (IS), Social Factors, encapsulated by the concept of subjective norms, have been consistently demonstrated to significantly affect an individual's behavioral intention to adopt a technology (Venkatesh et al., 2003). The observation of peers actively engaging in a technology often triggers a desire to align oneself with the group, thereby promoting adoption. This phenomenon is recognized in theoretical frameworks, such as the Theory of Planned Behavior (Ajzen, 1991), in which subjective norms are postulated as key determinants of behavioral intention. UTAUT (Venkatesh et al., 2003) further supports this, emphasizing the positive influence of social influence on technology adoption intentions.

Numerous empirical studies echo these theoretical underpinnings, demonstrating the extensive influence of social factors on various behavioral outcomes including the adoption of Internet sports gambling (Chiu et al., 2012), online payment systems (Wei et al., 2021), and mobile payment technologies (de Luna et al., 2019). Drawing parallels from these findings, it is reasonable to anticipate that social influence will stimulate students' intention to use microlearning.

Therefore, we propose the following hypothesis: *H2b: Social influence positively affects students' microlearning use intention.*

3.2 Effects of Cost Factors

3.2.1 Effect of Perceived Ease-of-Use on Perceived Value. Perceived ease-of-use reflects the extent to which an individual anticipates that using a particular system will be free of physical and mental effort (Davis, 1989). In the e-learning context, this amounts to students' belief that engaging with the educational approach will be effortless and straightforward (Lee, 2006). This positive association between perceived ease-of-use and perceived value is empirically verified in various domains (Avcilar & Özsoy, 2015; Ozturk et al., 2016; Yang & Lee, 2010).

Microlearning, characterized by its brevity and flexibility in content selection, offers students unparalleled convenience in overcoming geographical and temporal constraints (Lv et al., 2020). These attributes streamline the learning process, and contribute to a more efficient and stress-free experience, thereby enhancing students' perception of the value offered by microlearning.

Given this background, we hypothesize that: *H3a: Perceived Ease-of-Use positively affects students' Perceived Value of microlearning.*

3.2.2 Effect of Perceived Ease-of-Use on Use Intention. Analogous to perceived usefulness, perceived ease-of-use serves as a pivotal determinant in TAM (Davis, 1989), consistently emerging as a potent predictor of technology adoption behavior among diverse user populations (Yang et al., 2016). A vast amount of empirical research emphasizes a robust positive correlation between perceived ease-of-use and behavioral intention (Davis, 1989; Venkatesh & Davis, 2000).

In the e-learning domain, this positive influence is prominent, as perceived ease-of-use has been empirically verified to significantly enhance students' intention to utilize e-learning platforms (Jaiyeoba & Iloanya, 2019; Lee, 2006; Salimon et al., 2023). Thus, it is logical to hypothesize that the same dynamic applies to microlearning, where students' perceived ease-of-use will positively influence their intention to engage with the educational approach.

Therefore, we propose the following hypothesis: *H3b: Perceived Ease-of-Use positively affects students' microlearning Use Intention.*

3.2.3 Effect of Perceived Cost on Perceived Value. Zeithaml (1988) distinguishes perceived sacrifice into monetary and non-monetary dimensions. The monetary aspect relates to the direct financial investment required for a product, whereas the non-monetary facet includes a multitude of costs such as time, dissatisfaction, risk, effort, and the opportunity cost associated with consuming the product (Kim et al., 2007). In our study, we focus exclusively on the monetary dimension of perceived sacrifice, specifically perceived cost, which represents students' anticipated financial burden when considering the use of microlearning. This focus on monetary costs is supplemented by the recognition that perceived ease-of-use captures non-monetary costs, particularly the effort involved in using technology.

The extant literature demonstrates a negative correlation between perceived cost and perceived value, with some scholars suggesting that heightened perceptions of sacrifice may lead to a diminished or even unfavorable evaluation of services, as exemplified in the ride-hailing industry (Lu & Wang, 2020). Multiple empirical studies have validated the significant association between perceived fees and perceived value of products or service (Kim & Han, 2011). Notably, the perceived fee has been found to have a pronounced negative impact on perceived value (Kim & Kyung, 2023; Yoon & Oh, 2022), as illustrated by the pivotal role of price in shaping consumers' perceived value and their willingness to repurchase street food (Seo & Lee, 2021).

Therefore, we predict that the perceived cost of microlearning will likewise diminish students' perceived value of the educational approach. Hence, we formulate the following hypothesis: *H4a: Perceived Cost negatively affects students' Perceived Value of microlearning.*

3.2.4 Effect of Perceived Cost on Use Intention. The monetary costs associated with the acquisition, installation, and ongoing support of novel technologies are widely recognized as formidable barriers to their adoption (Hong et al., 2020). Scholars regard the associated fee as individuals' perceived sacrifice necessary to gain access to a particular service, emphasizing its role as a determinant of technology adoption decisions (Kim et al., 2007). For instance, economic factors have been identified as pivotal determinants of mobile payment system adoption (Yang, 2009). Similarly, perceived service fees significantly influence users' adoption intentions regarding mobile platforms for medical and senior care (Xiong & Zuo, 2023).

In the microlearning domain, which is frequently used for personal development and enrichment, students are inevitably confronted with the monetary costs associated with its use. Consequently, perceived cost plays a prominent role in shaping their willingness to adopt microlearning. When considering the adoption of the educational approach, perceived cost emerges as a primary constraint that influences the decision-making process.

Thus, we propose the following hypothesis: *H4b: Perceived cost negatively affects students' microlearning use intention.*

3.3 Effects of Perceived Value

The adoption of individual technologies requires a thorough evaluation of related perceptions. Central to this evaluation process is perceived value, a crucial indicator of adoption intention. Perceived value encapsulates the overall utility derived from a comparison of the perceived benefits and sacrifices associated with technology (Kim et al., 2007). In the information and communication technology domain, perceived value has been recognized as a powerful predictor of behavioral intention in various sectors including web-based (Chen & Dubinsky, 2003) and mobile services (Kim & Han, 2011; Kim et al., 2007).

Similarly, it is reasonable to assume that students' decisions to engage with microlearning will be significantly influenced by their perceived value of the educational approach.

Therefore, we propose the following hypothesis: *H5: Perceived value positively affects students' microlearning use intention.*

Based on the hypotheses outlined in this section, we present our research model in Figure 1. This model integrates the various factors and relationships that we hypothesize affect students' adoption of microlearning, thereby providing a comprehensive framework for our investigation.

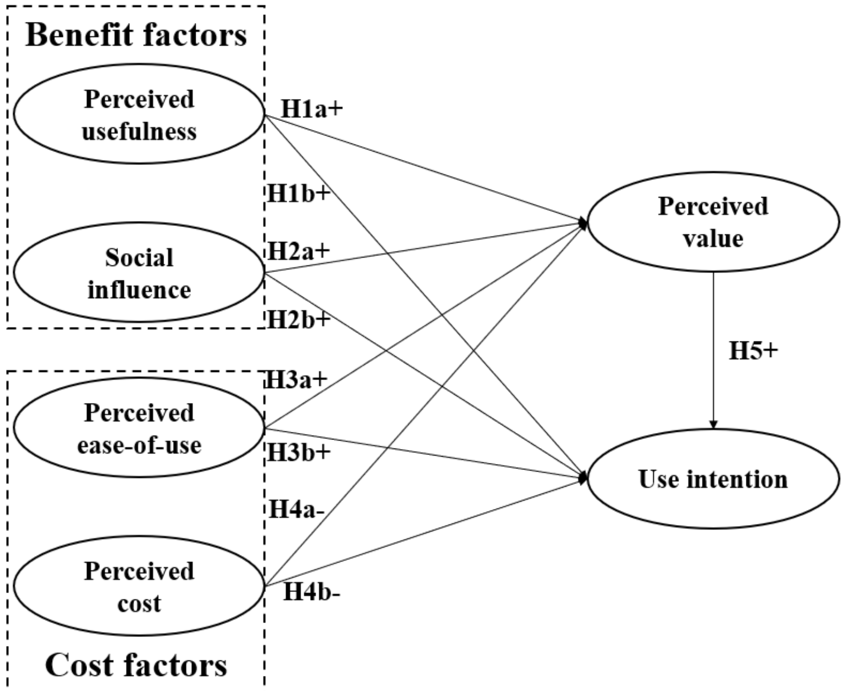


Figure 1. Research Model and Hypotheses

4. RESEARCH METHODS

4.1 Data Collection and Variable Measurement

We employed a questionnaire survey methodology, leveraging an online questionnaire primarily distributed through the platform https://www.wjx.com. In the questionnaire, we introduced the concept of microlearning to the participants to familiarize them with it (see Appendix A). Furthermore, we presented pictures and explanations of a microlearning platform (https://www.vko.cn/) to help participants better understand the context (see Appendix B). The microlearning platform includes courses in a university academic program, extensions for non-degree students, and commercial offerings. Subsequently, we requested that participants answer our survey based on the microlearning platform we introduced. The questionnaire asked about participants' demographic characteristics and focused on measures of key variables pertinent to the research objectives.

To ensure the reliability and validity of the measures, we employed well-established measurement items from the extant literature, which were adapted to accommodate the features of our study (see Table A1 in Appendix C). Each variable was assessed using four items evaluated on a five-point Likert scale. Specifically, the items for perceived usefulness, perceived cost, and perceived value were adapted from Yoon and Oh (2022). Perceived ease-of-use was assessed using items from Venkatesh et al. (2003), social influence with items from Wijaya et al. (2022), and use intention with items derived from Davis (1989).

We collected 334 questionnaires for this study. After excluding those where the answer time was too short or too long, where the answers were contradictory, and where answers to the attention check questions were incorrect, 320 valid samples were retained for subsequent analysis. The demographic profile of our sample reveals a predominantly younger and highly educated cohort: 45% of participants are female, 36.56% are aged in the range 21-30 years, 74.38% have a bachelor's degree or higher, and 89.06% report familiarity with microlearning. The demographic composition of our sample aligns closely with the typical online education user profile and indicates a profound understanding of microlearning, thereby ensuring a reasonable degree of representativeness of the study's target population. Before testing the hypotheses, we affirmed the reliability (Table 2) and validity (Table 3) of the items by employing *SmartPLS 3.0*, ensuring a solid foundation for the subsequent analysis.

Potential Factor	Items	Mean	Standard Deviation	Standard Factor Loading	CR	AVE	Cronbach's α
Perceived usefulness (PU)	PU1	3.428	1.361	0.822	0.890	0.669	0.890
	PU 2	3.450	1.336	0.853			
	PU3	3.462	1.362	0.788			
	PU4	3.422	1.421	0.808			
Perceived ease-of-use (PEOU)	PEOU1	3.584	1.313	0.809	0.865	0.616	0.864
	PEOU2	3.575	1.321	0.786			
	PEOU3	3.597	1.377	0.817			
	PEOU4	3.538	1.334	0.725			
Social influence (SI)	SI1	3.513	1.365	0.839	0.890	0.670	0.890
	SI2	3.422	1.335	0.824			
	SI3	3.500	1.383	0.780			
	SI4	3.441	1.406	0.829			
Perceived cost (PC)	PC1	2.400	1.343	0.810	0.856	0.598	0.855
	PC2	2.453	1.267	0.773			
	PC3	2.516	1.325	0.776			
	PC4	2.438	1.324	0.732			
Perceived value (PV)	PV1	3.487	1.337	0.787	0.880	0.649	0.880
	PV2	3.534	1.398	0.783			
	PV3	3.587	1.343	0.834			
	PV4	3.544	1.341	0.812			
Use Intention (UI)	UI1	3.456	1.332	0.769	0.868	0.622	0.870
	UI2	3.569	1.390	0.837			
	UI3	3.538	1.284	0.769			
	UI4	3.566	1.345	0.778			

Table 2. Reliability Test Results

	PC	PEOU	PU	PV	SI	UI
PC	0.814					
PEOU	-0.061	0.843				
PU	-0.083	0.600	0.867			
PV	-0.070	0.508	0.554	0.858		
SI	-0.005	0.476	0.461	0.445	0.867	
UI	-0.019	0.583	0.570	0.542	0.607	0.848

Table 3. Validity Test Results

The results in Table 2 indicate that all the standard factor loadings exceed 0.7. The composite reliability (CR) values range from 0.856 to 0.890, well above the recommended minimum threshold of 0.6. In addition, the average variance extracted (AVE) values are all above the benchmark of 0.5. Moreover, Cronbach's α coefficients for all variables surpass the threshold of 0.8, confirming strong internal reliability.

As Table 3 shows, the correlation coefficients between the variables were consistently lower than the square roots of their respective AVE values. This pattern confirms the discriminant validity of the questionnaire, indicating that the items effectively differentiate between distinct latent constructs.

4.2 Structural Equation Model: Path Analysis

To test our hypotheses, we employed structural equation modeling (SEM) using *SmartPLS 3.0* software to conduct the path analysis. The model fit indices obtained were: SRMR=0.048, d_ULS=0.950, d_G=0.417, and NFI=0.845. Specifically, the SRMR value of 0.048 for this study framework met the criterion of SRMR<0.08 (Henseler et al., 2016). The t-values were computed using a bootstrapping procedure with 5,000 samples. The PLS estimation results, including the path coefficients, t-statistics, significance levels of the constructs, and hypotheses testing outcomes are detailed in Table 4.

Causal path	Beta Coefficient	Standard Deviation	T Statistics	P Values	Hypotheses testing
H1a: Perceived Usefulness -> Perceived Value	0.337***	0.071	4.709	0.000	Supported
H1b: Perceived Usefulness -> Use Intention	0.183***	0.065	2.821	0.005	Supported
H2a: Social Influence -> Perceived Value	0.187***	0.056	3.338	0.001	Supported
H2b: Social Influence -> Use Intention	0.346***	0.050	6.996	0.000	Supported
H3a: Perceived Ease-of-Use -> Perceived Value	0.216***	0.070	3.086	0.002	Supported
H3b: Perceived Ease-of-Use -> Use Intention	0.229***	0.061	3.740	0.000	Supported
H4a: Perceived Cost -> Perceived Value	-0.025	0.062	0.442	0.658	Not supported
H4b: Perceived Cost -> Use Intention	0.019	0.051	0.361	0.718	Not supported
H5: Perceived Value -> Use Intention	0.193***	0.061	3.112	0.002	Supported
Gender -> Use Intention	-0.027	0.038	0.672	0.501	—
Age -> Use Intention	0.012	0.046	0.230	0.818	—
Education -> Use Intention	-0.093**	0.037	2.516	0.012	—
Experience -> Use Intention	0.012	0.040	0.271	0.786	—

Note: ***p<0.01, **p<0.05, *p<0.1.

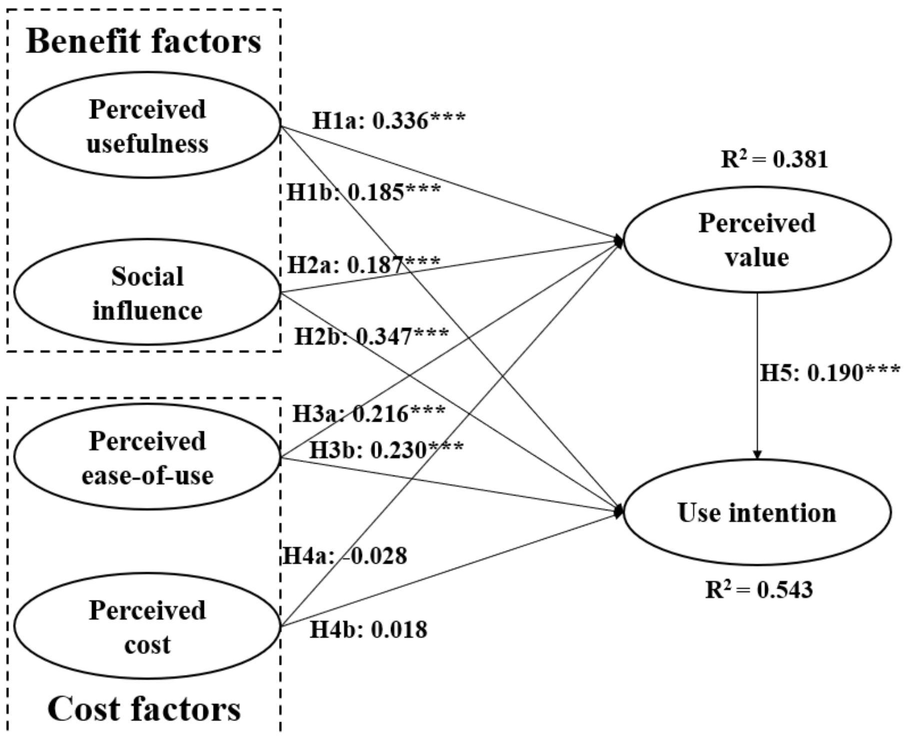
Table 4. Path Analysis

Figure 2 shows the relationships between variables and their statistical significance. We included control variables such as gender, age, education, and microlearning experience. To maintain a clear and concise visualization, these control variables are not shown in Figure 2. Our analysis reveals intriguing insights into the influence of benefit and cost factors on perceived value and use intention. Specifically, among the benefit factors, both perceived usefulness and social influence exhibit significant positive effects on both perceived value (β=0.336, t=4.779, p<0.01; β=0.187, t=3.416, p<0.01) and use intention (β=0.185, t=0.184, p<0.01; β=0.347, t=7.354, p<0.01), thereby validating H1a, H1b, H2a, and H2b.

However, in contrast to the benefit factors, the impact of the cost factors is more nuanced. Among the cost factors, only perceived ease-of-use demonstrated significant positive effects on both perceived value

(β=0.216, t=3.099, p<0.01) and use intention (β=0.230, t=3.671, p<0.01), supporting H3a and H3b. Conversely, the effects of perceived cost on both perceived value (β=-0.028, t=0.432, p=0.666) and use intention (β=0.018, t=0.356, p=0.722) were found to be statistically insignificant; thus, H4a and H4b are not supported. Furthermore, our analysis highlights the significant positive influence of perceived value on use intention (β=0.190, t=3.188, p<0.01), confirming H5.

The R^2 of 0.381 for perceived value indicates that perceived usefulness, social influence, perceived ease-of-use, and perceived cost collectively explain 38.1% of its variance, highlighting the significant role of these 4 factors. Furthermore, perceived value accounts for 54.3% of the variance in use intention, demonstrating its strong explanatory power.



Note: ***p<0.01, **p<0.05, *p<0.1.

Figure 2. Research Model Test Results

5. CONCLUSION AND DISCUSSION

5.1 Key Findings

Drawing on TAM and PVM, this study constructed a framework to delve into the antecedents that shape students' intention to use microlearning. By analyzing a dataset comprising 320 validated survey responses using SEM, the following key findings were obtained.

First, our investigation validates that both perceived usefulness and perceived ease-of-use positively contribute to students' intention to use microlearning. This corroborates TAM, which posits that these two factors are crucial determinants of behavioral intention (Davis, 1989). Our results also align with prior IS research emphasizing the utilitarian dimension as a significant driver of IS acceptance (Kim & Han, 2011) and echo research in e-learning that emphasizes the significance of easy system operability in fostering adoption intention (Salimon et al., 2023).

Second, social influence emerges as a potent factor, exhibiting the strongest direct effect on students' intention to use microlearning. This emphasizes the influence of social norms and desire for social identity as individuals seek to align themselves with their peers' behaviors and attitudes (Ajzen, 1991). Our findings resonate with previous studies highlighting the positive impact of social factors on various behavioral outcomes (Chiu et al., 2012; de Luna et al., 2019; Wei et al., 2021) and specifically echo Jiang et al.'s (2022) observation of the paramount role of peer influence in shaping perceived value.

Third, we found that perceived cost has an insignificant effect on students' intention to use microlearning. This deviation from prior studies that emphasize the role of economic factors (Xiong & Zuo, 2023; Yang, 2009) may stem from the ubiquitous availability of free microlearning and accessible WiFi, effectively negating monetary barriers to adoption. This aligns with global trends in open access education. Furthermore, monetary costs may be shifted from end users to educational providers. For instance, universities often absorb microlearning fees.

Fourth, our analysis reveals that perceived usefulness, perceived ease-of-use, and social influence positively influence perceived value. This emphasizes that when students perceive microlearning as beneficial, user-friendly, and socially accepted, they assign it a higher value. Our findings are congruent with prior research demonstrating the positive impact of these factors on perceived value (Ozturk et al., 2016; Zhang et al., 2019).

Finally, we confirm that perceived value significantly enhances students' intention to use microlearning. This aligns with the widely held belief that perceived value is a pivotal predictor of adoption intentions (Chen & Dubinsky, 2003; Zeithaml, 1988) and is supported by empirical evidence (Alam et al., 2023; Seo & Lee, 2021). This conclusion is consistent with behavioral decision theory, which posits that individuals weigh the costs and benefits of their decisions, such as the effort invested and quality of the outcome (Payne, 1982).

5.2 Theoretical Implications

Our study offers several theoretical implications by integrating TAM and PVM to analyze students' intention to use microlearning. First, it introduces a novel and comprehensive framework tailored to the microlearning domain, which integrates both benefit (perceived usefulness and social influence) and cost (perceived ease-of-use and perceived cost) factors. This framework provides a nuanced understanding of microlearning adoption dynamics by considering both technological (perceived usefulness, perceived ease-of-use) and social dimensions (social influence). By reclassifying the core variables of TAM into a dual cost-benefit structure and incorporating the central mediator of PVM—perceived value—we bridge the gap between functional and value-based perspectives. This integration enriches the theoretical landscape by addressing TAM's limited consideration of financial barriers, social influences, and attitude.

Second, our findings extend TAM by empirically validating the predictive power of perceived usefulness and perceived ease-of-use on the intention to use microlearning in this context. By substituting the traditional "attitude" construct with perceived value, we offer a cost-benefit perspective on intention formation, thereby enriching the mechanism through which individuals form adoption intentions. This contribution not only strengthens the TAM but also demonstrates its adaptability and applicability in diverse technological contexts.

Last, our research contributes to PVM by exploring its antecedents and consequences in the microlearning context. We extend the model by considering both monetary (perceived cost) and non-monetary costs (perceived ease-of-use), as well as technological (perceived usefulness) and social (social influence) utilities. By confirming the positive impact of perceived value on the intention to use microlearning, we strengthen the model's applicability and relevance in explaining technology adoption. This study enhances the theoretical foundation of PVM and provides valuable insights into the underlying mechanisms that drive adoption intentions in the digital education landscape.

5.3 Practical Implications

Our findings offer actionable insights for key stakeholders in the microlearning ecosystem, including educators, instructional designers, and ed-tech developers responsible for platform optimization. First, to enhance students' use intention, stakeholders should prioritize improving the perceived utility of microlearning. Given that perceived usefulness is positively correlated with both perceived value and use intention, instructional designers can focus on improving the functionality and relevance of microlearning to better meet students' learning needs. By highlighting these enhancements, educators can increase students' perceived usefulness, subsequently boosting their perceived value and intention to use microlearning. To achieve this, course designers could closely align microlearning content with current industry trends, job requirements, or academic curricula to ensure it addresses real-world needs. In addition, providing case studies, project-based learning opportunities, and practical exercises that demonstrate how microlearning skills can be applied in real-life scenarios would further enhance the perceived relevance of these courses. Moreover, implementing feedback loops, where students can provide input on course content and usability, would enable continuous improvement and help maintain courses' engagement and effectiveness. Educators, on the other hand, could help students adopt microlearning by showcasing its effectiveness through examples or data.

Second, stakeholders need to address the factors that hinder students' adoption of microlearning. Our results indicate that perceived ease-of-use significantly influences their perceived value and use intention. If students perceive microlearning as difficult to use, their perceived value and intention to adopt may decline. Therefore, ed-tech developers should endeavor to simplify the user experience and align it with students' usage habits to minimize barriers to adoption. For example, course designers could design an intuitive interface with clear navigation menus and simple operation steps and ensure that microlearning is fully compatible with mobile devices. In addition, both course designers and educators could offer user guides or short tutorial videos to help students quickly become familiar with microlearning and feel more comfortable using it. To this end, they could provide readily accessible support resources such as FAQs, help centers, and responsive customer service to assist learners when they encounter difficulties.

Third, stakeholders can leverage social influence to encourage students' adoption of microlearning. Beyond technological factors, our findings emphasize the important role of social influence in shaping their perceived value and use intention. By showcasing positive attitudes and actual usage among their peers, educators can harness the power of social influence to increase students' perceived value and intention to use microlearning. For example, designers can introduce gamification elements, such as badges and leaderboards, to motivate students to complete courses and refer others. They could also design interactive microlearning that encourages social media sharing and peer collaboration, thereby boosting engagement. Educators can amplify positive student experiences through testimonials and discussions, and foster communities around microlearning using forums and study groups for shared learning and mutual support. This approach can help create a supportive and encouraging environment that promotes the adoption of microlearning.

5.4 Limitations and Future Research Directions

Our study also has some limitations that offer promising avenues for future research. First, our investigation focused solely on students' use intention, without capturing actual use behavior. In a real-world context, certain factors may limit the generalizability of our findings. Thus, future studies could delve more deeply by collecting data on students' actual use patterns or conducting field experiments to observe their behavior in situ.

Second, our analysis considered a limited set of factors influencing use intention. Other crucial variables such as perceived time cost, perceived fun, perceived interactivity, and individual personality traits were not included in our model. Future research efforts could explore these and other factors to provide a more comprehensive picture of the multifaceted nature of microlearning adoption.

Third, our study focused on the explanatory power of perceived value in predicting use intention. The relative predictive capability of perceived value compared to other constructs, especially the "attitude" construct central to TAM, remains unclear. Future research could therefore undertake comparative analyses to determine the relative influence of perceived value and other constructs on use intention or uncover alternative antecedents with even greater explanatory potential.

Last, while our exclusive focus on the student perspective provides valuable insights, this approach does not capture the influential role of teachers as gatekeepers and facilitators in educational technology adoption. As such, future research could adopt a dual-stakeholder approach to contrast student and teacher perspectives, particularly examining how teacher-related variables—such as teaching self-efficacy, digital literacy, or pedagogical alignment with microlearning—shape students' perceptions of usefulness, ease-of-use, and perceived value.

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APPENDICES

Appendix A. Definition of Microlearning in the Questionnaire

In our questionnaire, the concept of microlearning is defined as follows:

Microlearning is multimedia-rich resources capturing the dynamic teaching and learning interactions of educators in various settings, whether within the classroom or beyond. These courses concentrate on a single knowledge point—be it a key concept, a challenging topic, or a point of confusion—and are designed to address a specific teaching segment. Characterized by their contextual relevance, brevity, thematic clarity, and precision, micro-courses are an innovative educational approach. To encapsulate, microlearning embodies a fresh paradigm in online education, distinguished by their short, yet highly concentrated, instructional video content.

Appendix B. Screenshots and Descriptions of the Microlearning Platform in the Questionnaire

The pictures and explanations of the microlearning platform presented in our questionnaire are as follows:

(1) Users need to register and log in to their accounts for each study session (as shown in Figures A1 and A2).

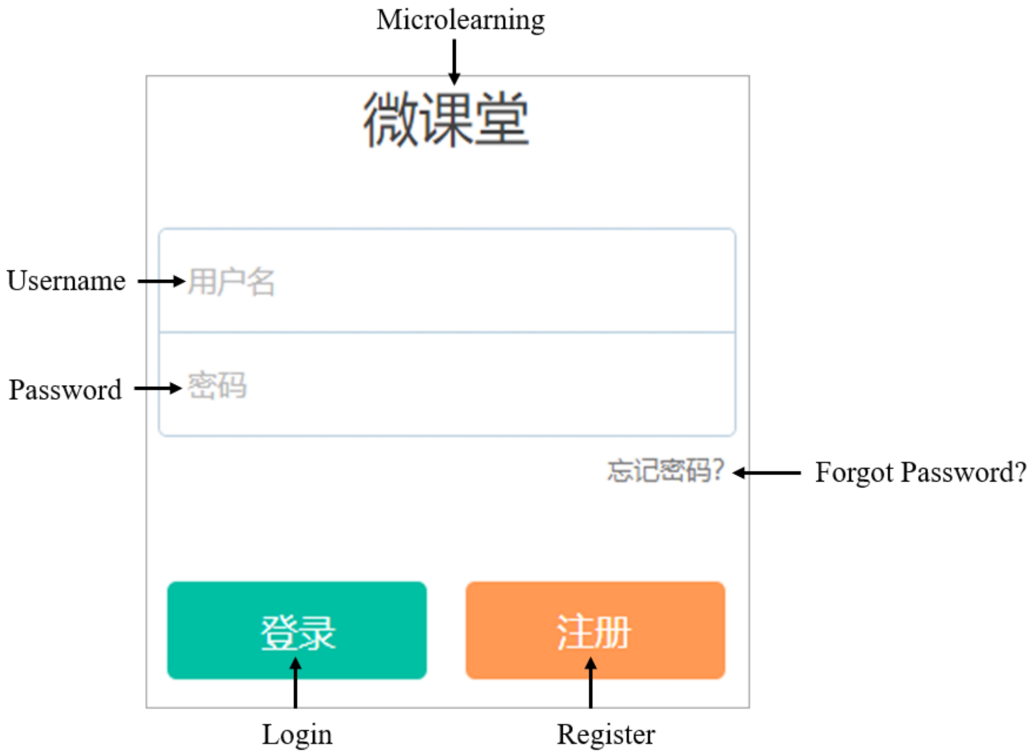

Figure A1. Screenshot of the Login Page of the Platform

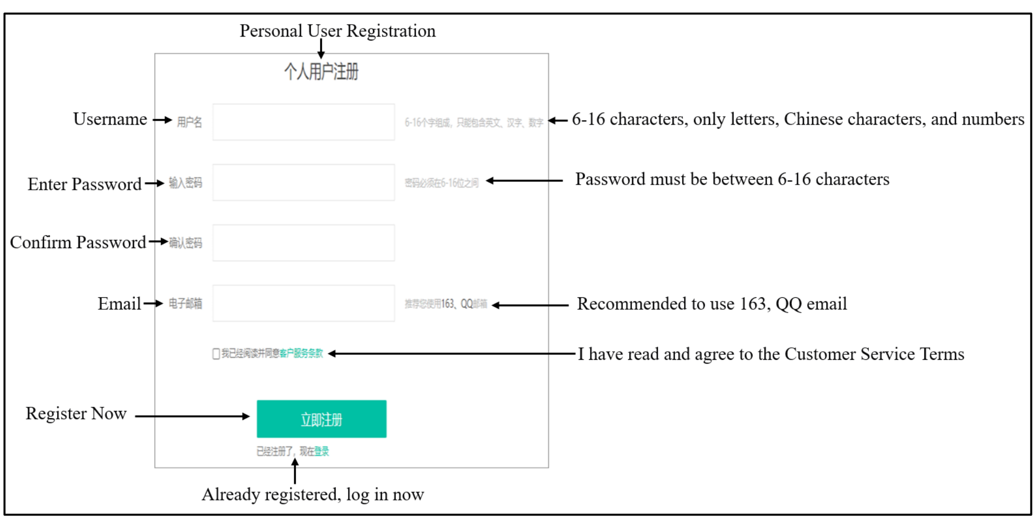

Figure A2. Screenshot of the Registration Page of the Platform

(2) A search box is set on the home page, allowing users to quickly find the courses they need (as shown in Figure A3).

Figure A3. Screenshot of the Homepage of the Platform

(3) When the required knowledge points are clicked on the video playback interface, the playback starts (as shown in Figure A4).

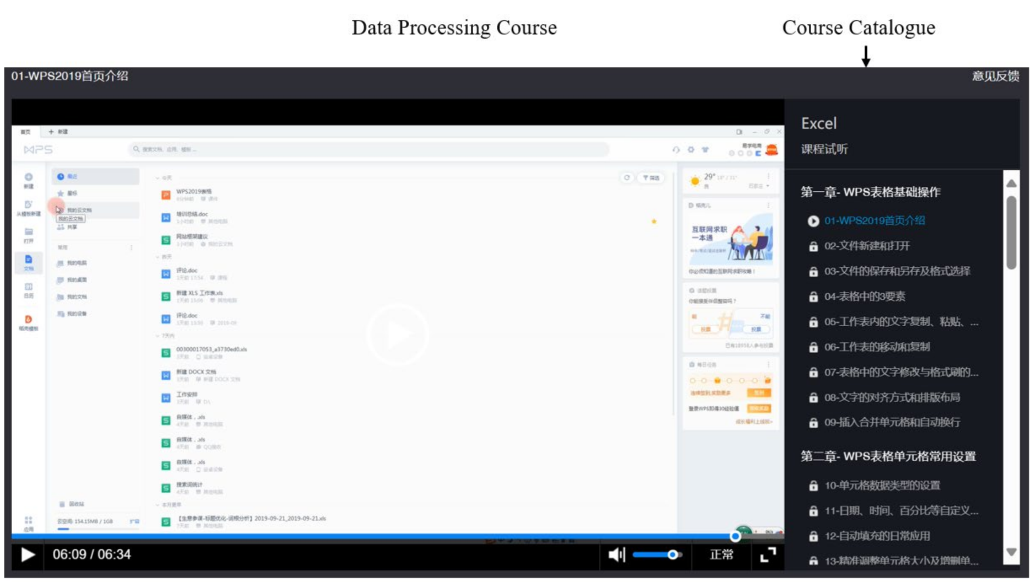

Figure A4. Screenshot of a Course-Playing Page on the Platform

(4) Support multiple learning terminals (as shown in Figure A5).

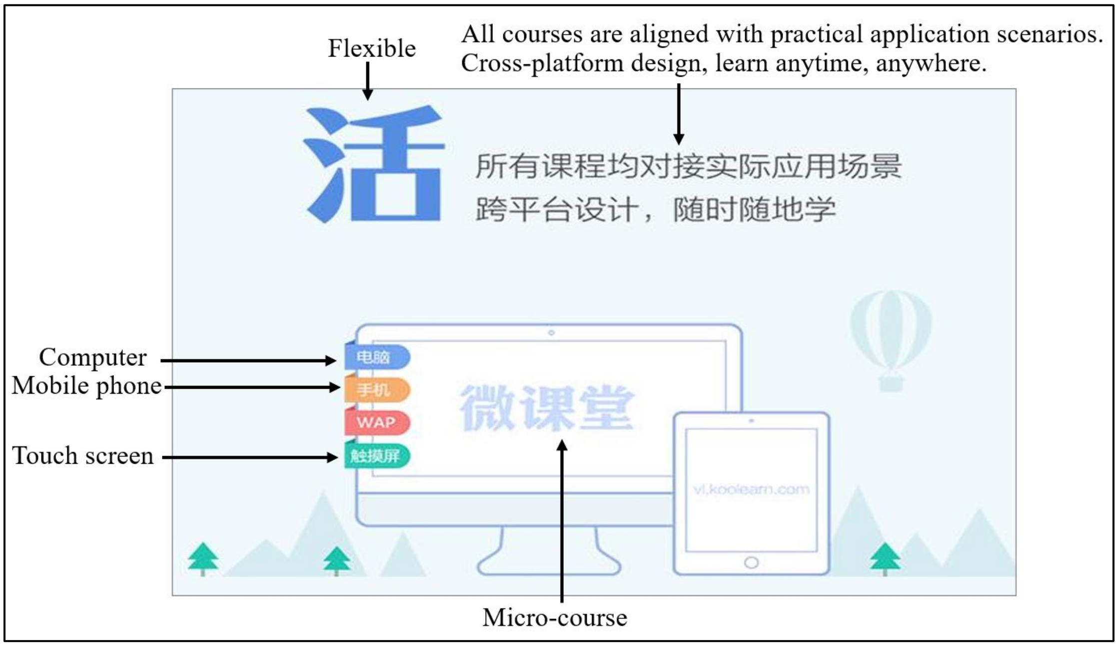

Figure A5. Screenshot of the Learning Terminal's Introduction Page on the Platform

(5) The duration of microlearning videos is short (as shown in Figure A6).

Figure A6. Screenshot of the Course Duration Introduction Page on the Platform

(6) The main providers of course resources are all carefully selected renowned teachers (as shown in Figure A7).

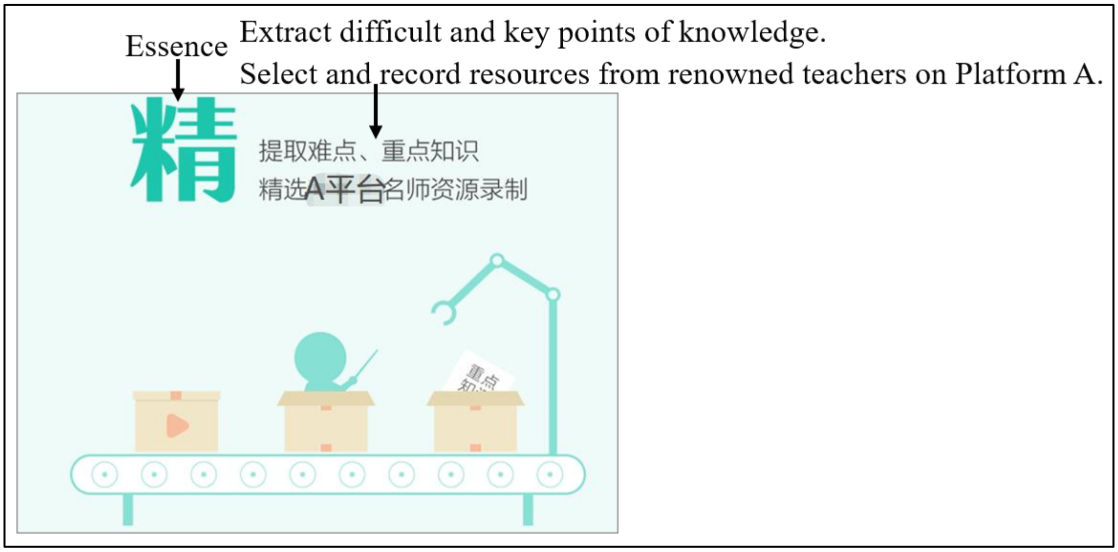

Figure A7. Screenshot of the Introduction to Course Quality Page on the Platform

(7) Most courses are free of charge. Only a few excellent courses are charged for (as shown in Figure A8).

Figure A8. The Screenshot of the Microlearning Fees Page on the Platform

Appendix C. Measurement Items

Variables	Items	Measurement items	Reference
Perceived usefulness (PU)	PU1	I think microlearning helps with my learning.	Yoon & Oh (2022)
	PU 2	I think microlearning improves my learning.	
	PU3	I think microlearning enhances my performance in learning.	
	PU4	I think microlearning is useful for my learning.	
Perceived ease-of-use (PEOU)	PEOU1	I think the operation process of using microlearning is simple and easy to understand.	Venkatesh et al. (2003)
	PEOU2	I think the operation to open and watch microlearning is straightforward.	
	PEOU3	I can grasp various functions and login methods of microlearning platforms.	
	PEOU4	I think microlearning is very convenient to use.	
Social influence (SI)	SI1	People around me use microlearning.	Wijaya et al. (2022)
	SI2	People around me encourage me to use microlearning.	
	SI3	Social media encourages me to use microlearning.	
	SI4	Using microlearning will increase my social status.	
Perceived cost (PC)	PC1	I think the cost of the equipment for microlearning is high.	Yoon & Oh (2022)
	PC2	I think the price of microlearning is high.	
	PC3	I think the data charges for microlearning are high.	
	PC4	I think the cost associated with using microlearning is high.	
Perceived value (PV)	PV1	I think the output compared to the cost of microlearning is valuable.	Yoon & Oh (2022)
	PV2	I think the output compared to the effort of microlearning is valuable.	
	PV3	I think the output compared to the time spent on microlearning is valuable.	
	PV4	I think the output of microlearning is valuable.	
Use Intention (UI)	UI1	I will consider microlearning as my first choice when necessary.	Davis (1989)
	UI2	I intend to use microlearning to learn when necessary.	
	UI3	I am willing to persist in using microlearning when necessary.	
	UI4	I intend to recommend microlearning to classmates or friends.	

Table A1. Measurement Items

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