

Article

Examining the Effects of Habit and Self-Efficacy on Users' Acceptance of a Map-Based Online Learning System via an Extended TAM

Wenhui Xu ¹, Ke Zhu ^{1,2}, Dongbo Zhou ^{3,*}, Chunli Wang ¹ and Chaodong Wen ³¹ Faculty of Education, Henan Normal University, Xinxiang 453007, China² Henan Collaborative Innovation Center for Intelligent Education, Henan Normal University, Xinxiang 453007, China³ Faculty of Artificial Intelligence in Education, Central China Normal University, Wuhan 430079, China

* Correspondence: zhoudongbo@ccnu.edu.cn

Abstract

Digital maps have become important teaching and learning tools in education. However, limited research has examined the factors influencing learners' acceptance of map-based online learning systems. This study proposes and validates an extended Technology Acceptance Model (TAM) that integrates two psychological constructs—habit and self-efficacy—into the original TAM framework to better explain students' behavioural intention to use a map-based online learning system (Map-OLS). Structural equation modelling (SEM) was employed to analyse data from 812 participants with prior online learning experience. The results indicated that perceived ease of use (PEoU) and perceived usefulness (PU) had direct positive effects on the behavioural intention to use Map-OLS. PEoU positively affected PU and indirectly influenced behavioural intention to use Map-OLS via PU. Both habit and self-efficacy had significantly positive influences on PEoU and PU. Self-efficacy also directly influenced the behavioural intention to use Map-OLS. This study makes a theoretical contribution by extending and empirically validating TAM in the context of map-based learning environments, while also offering practical insights for designing more engaging and effective online learning systems.



Academic Editor: Radhi Al-Mabuk

Received: 30 May 2025

Revised: 22 June 2025

Accepted: 25 June 2025

Published: 1 July 2025

Citation: Xu, W., Zhu, K., Zhou, D., Wang, C., & Wen, C. (2025). Examining the Effects of Habit and Self-Efficacy on Users' Acceptance of a Map-Based Online Learning System via an Extended TAM. *Education Sciences*, 15(7), 828. <https://doi.org/10.3390/educsci15070828>

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Keywords: online learning; map-based online learning system; technology acceptance model; structural equation model; behavioural intention

1. Introduction

Online learning has become a widely adopted educational mode in recent years (Feldman-Maggor et al., 2024; Zheng et al., 2020), particularly in the wake of the COVID-19 pandemic, which accelerated the digital transformation of teaching and learning worldwide (Anders et al., 2024; Shirish et al., 2021). Although online learning offers multiple advantages, such as flexible access, reduced educational costs, and expanded learning opportunities (Panigrahi et al., 2018; van Haastrecht et al., 2024), it continues to face long-standing challenges, especially in terms of learner engagement, motivation, and high attrition rates (Henrie et al., 2015; Perna et al., 2014).

A key contributor to these challenges is the way online learning resources are typically structured and delivered. The prevailing linear or hierarchical presentation styles, such as table links or syllabus-based directories, often limit learners' autonomy and diminish their intrinsic motivation (Lau et al., 2018). These traditional content layouts make it difficult

for learners to navigate, discover connections between concepts, or maintain sustained interest in the course material (DuHadway & Henderson, 2015). Addressing these concerns necessitates exploring alternative organizational methods that can actively engage learners and boost their motivation in online environments. Recent research has called for more innovative, interactive, and visually enriched systems that promote exploratory learning and increase student engagement (Zhao & Yang, 2023).

One promising avenue of exploration involves the utilization of a map-based online learning system (Map-OLS). This system leverages the visual-spatial features of digital maps to organize learning resources and construct knowledge structures in a more interactive and learner-centric manner. In contrast to traditional menu-based systems, Map-OLS presents learners with a knowledge map that enables them to explore, navigate, and interact with content based on their preferences. Prior studies have suggested that knowledge maps can enhance student interest and engagement more effectively than traditional outlines (Araos et al., 2023; Ullah, 2020). Furthermore, individuals accustomed to utilizing maps in their daily routines may cultivate ingrained behaviours and inclinations for spatially arranged content, potentially heightening their sense of autonomy and motivation within digital learning environments (Ma et al., 2021).

This study focuses on Map-OLS, a map-based online learning system that combines the structural advantages of knowledge maps with the intuitive navigation features of location-based services. Map-OLS enables learners to access and organize knowledge points through a visual, interactive interface designed to promote meaningful learning engagement. According to Self-Determination Theory, sustained learner engagement requires fulfilling three fundamental psychological needs: autonomy, competence, and relatedness (Chiu, 2021, 2022). Map-OLS inherently supports these needs by providing interactive visual guidance (competence), enabling self-directed navigation and learning choices (autonomy), and potentially supporting interactions within the learning community (relatedness). Thus, the use of map-based approaches for organizing and managing learning resources in online learning environments may offer a meaningful avenue for addressing issues related to insufficient learner motivation and low engagement.

Map-OLS is a category of systems integrating visual navigation to enrich personalized and adaptable learning experiences. While learning management systems, mobile learning tools, and Massive Open Online Courses (MOOCs) have been extensively studied through the lens of Technology Acceptance Models (Panjaburee et al., 2022; Sui et al., 2023), empirical research on user acceptance of map-based online learning environments is limited. Understanding the factors influencing learners' adoption and use of systems like Map-OLS is crucial for their successful implementation and meaningful utilization (Al-Fraihat et al., 2020). Moreover, limited attention has been given to psychological factors, such as habits and self-efficacy, which may influence learners' intentions to engage in innovative learning systems. To address this research gap, this study employs the Technology Acceptance Model (TAM), a well-established theoretical framework predicting technology acceptance based on perceived usefulness (PU) and perceived ease of use (PEoU) (Davis, 1989). By extending TAM to integrate habit and self-efficacy as additional determinants, this research aims to provide a comprehensive understanding of learners' intentions to accept and utilize Map-OLS.

Therefore, this study aims to investigate the following research question: What are the key factors influencing learners' behavioural intentions to use a map-based online learning system, and how do habit and self-efficacy interact with traditional TAM constructs in this context? To answer this question, this paper is organized as follows: Section 2 reviews the relevant literature on map-based online learning and Technology Acceptance Model; Section 3 presents the research and hypotheses; Section 4 describes the methods; Section 5

reports the empirical results; Section 6 discusses the findings, implications, and limitations; and Section 7 synthesizes the main findings of the study and highlights its key contributions to the field.

2. Literature Review

2.1. Map-Based Online Learning

Digital maps have long served as important tools for teaching and learning in higher education (Jones et al., 2004). In the context of online learning, map-based resource organization and visualization methods can be broadly categorized into two types: (1) conceptual/semantic maps, such as knowledge maps and concept maps, and (2) location-based services (LBSs) that use spatial metaphors for browsing learning (Liu et al., 2020).

The first category, knowledge maps, involves a node–link structure that represents key concepts and their semantic relationships. These visual tools, ranging from concept maps to mind maps, can support learners in identifying knowledge hierarchies, tracing conceptual dependencies, and building integrated knowledge frameworks (Lee & Segev, 2012). Empirical studies have shown that knowledge maps can improve learning satisfaction and performance more effectively than linear or hierarchical syllabus-based structures (Shaw, 2010). Additionally, the integration of microlearning with knowledge maps has been shown to enhance engagement and facilitate the development of structured knowledge (Ma et al., 2021). Knowledge maps enable learners to locate, retrieve, and contextualize learning content efficiently through visual cues and semantic structuring (Li et al., 2015).

The second category of such methods includes public SBSs, which focus on providing services based on the geographic location of mobile devices or humans (Brown et al., 2011); such SBSs include Google Maps and ArcGIS map services. In recent years, the handy browsing learning style and location-based mode of navigation have become dominant metaphorical approaches to online learning (Araos et al., 2023). For example, using course unit maps for online learning is similar to using public map services such as Google Maps in a daily context, which can enable students to grasp the meanings and relationships among course units quickly in an analogous and exploratory manner (Dang et al., 2011). Liu et al. (2020) developed MapOnLearn for online learning systems to employ a map-based organization and visualization method, which could support personalized learning and interactive learning as well as provide easy-to-access resources. Anshari (2016) emphasized that students should be empowered to participate in the learning process actively rather than being regarded merely as the recipients of information and knowledge. Barak and Ziv (2013) developed a location-based interactive learning platform and found that using this platform could enhance 21st-century skills.

To sum up, using map organization and visualization in online learning could not only attract learners' interests and meet their learning needs but also provide learners with personalized learning support and learning interaction. In this study, we define Map-OLS as a hybrid system that integrates the semantic structure of knowledge maps with the navigational interface of public SBSs. Specifically, Map-OLS organizes and manages learning resources across multiple levels of disciplinary content using a visual interface that mimics geographic exploration (e.g., Google Maps). While Map-OLS does not aim to construct a deep semantic ontology of knowledge, it qualifies as a functional knowledge map system in that it supports hierarchical organization, relationship mapping, and knowledge localization. The metaphorical exploration of course content through a spatial interface may promote learner engagement, autonomy, and understanding.

Despite its potential benefits, few empirical studies have investigated learners' acceptance of map-based online learning systems like Map-OLS. Existing studies have largely focused on learners' cognitive outcomes (e.g., performance, comprehension) while neglect-

ing the psychological and behavioural factors that influence system adoption. According to [Al-Emran et al. \(2018\)](#) and [Huang et al. \(2021\)](#), understanding how students accept and interact with learning technologies is crucial for optimizing their design and use in digital learning environments. Therefore, this study addresses this gap by investigating learners' behavioural intentions to use Map-OLS.

2.2. Technology Acceptance Model

Numerous theoretical models have been developed to explain and predict individuals' acceptance of new technologies or systems. Among them, the Technology Acceptance Model (TAM) proposed by [Davis \(1989\)](#) is one of the most widely applied frameworks in the context of information system adoption. TAM posits that users' behavioural intention to use a system is primarily determined by perceived usefulness (PU) and perceived ease of use (PEoU), core variables of TAM ([Marangunić & Granić, 2015](#)). According to the Theory of Reasoned Action, it is behavioural intentions rather than attitudes that are the main predictors of actual use behaviours ([Azjen, 1980](#)). The robustness and generalizability of TAM have been confirmed across diverse cultural and technological contexts (e.g., [Wu & Chen, 2017](#); [Joo et al., 2018](#); [Mohammadi, 2015](#)) and across application domains such as online learning, AI coding assistant tools, online meeting, and mobile libraries ([Pan et al., 2024](#); [Rafique et al., 2020](#); [Taş & Kiraz, 2023](#); [Voicu & Muntean, 2023](#)).

TAM has been extended through several significant iterations. For example, [Venkatesh and Davis \(2000\)](#) extended the original TAM by incorporating social influence processes (subjective norm, voluntariness, etc.) and cognitive instrumental processes (output quality, result demonstrability, and PEoU) to develop TAM2. By comparing other models, [Venkatesh et al. \(2003\)](#) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) and suggested that performance expectations, effort expectations, and social influence directly determine intention to use, and intention and facilitation conditions directly influence usage behaviours. In addition to these factors, [Venkatesh and Bala \(2008\)](#) further took into account the determinants of individual-level information technology adaptation and use and proposed an integrated model known as TAM3. [Venkatesh et al. \(2012\)](#) successively introduced hedonic motivation, price value, and habit into UTAUT and proposed UTAUT2, which represented a substantial improvement over UTAUT in explaining the differences in behaviour intentions. These extensions have improved the explanatory power of the original TAM in various contexts.

Although UTAUT2 and TAM3 offer comprehensive frameworks, they include broader behavioural and contextual constructs that may not be directly relevant in educational environments such as online learning systems. The original TAM focuses on cognitive evaluations, namely, perceived usefulness (PU) and perceived ease of use (PEoU), as primary predictors of behavioural intention. It does not explicitly account for individual behavioural patterns or psychological capabilities, which are crucial in self-directed online learning environments. Habit reflects the extent to which behaviour is performed automatically due to learning or repetition ([Dai et al., 2020](#)). In online learning systems like Map-OLS that require exploratory navigation, users with established map-using habits are more likely to perceive the system as both easy to use and useful. Habit has been empirically shown to directly influence both PEoU and PU ([Rafique et al., 2020](#); [Venkatesh et al., 2012](#)). Self-efficacy, defined as an individual's belief in their ability to execute specific tasks, plays a significant role in shaping learners' confidence and perceived competence in using technology ([Bandura & Wessels, 1997](#)). In online learning environments where teacher guidance is limited, learners' self-efficacy becomes critical for navigating learning resources, troubleshooting issues, and maintaining engagement ([Luo & Du, 2022](#)). Prior research has shown that self-efficacy positively affects both PEoU and PU ([Chahal & Rani,](#)

2022; Chen, 2014; Venkatesh & Bala, 2008). Thus, the present study retains the parsimony of the original TAM while selectively extending it by incorporating two empirically supported psychological constructs, habit and self-efficacy, which have been shown to influence PU and PEOU in technology adoption studies.

Therefore, this study aims to address this gap by extending the original TAM with the inclusion of habit and self-efficacy in order to better understand the psychological mechanisms underlying learners' behavioural intention to use Map-OLS. Specifically, it examines how these two factors affect learners' perceptions of usefulness and ease of use and, in turn, their behavioural intentions toward system adoption, as shown in Table 1.

Table 1. Summary of model constructs, hypotheses, and supporting literature.

Constructs	Role in Model	Hypothesized Path	Theoretical Basis
Perceived Usefulness (PU)	Core TAM variable	PU → BI	(Davis, 1989; Mohammadi, 2015)
Perceived Ease of Use (PEoU)	Core TAM variable	PEoU → PU; PEoU → BI	(Venkatesh & Davis, 2000; Wang et al., 2021)
Habit (HA)	External variable	HA → PEoU; HA → PU	(Rafique et al., 2020; Venkatesh et al., 2012)
Self-Efficacy (SE)	External variable	SE → PEoU; SE → PU	(Chahal & Rani, 2022; Chen, 2014; Venkatesh & Bala, 2008)
Behavioural Intention (BI)	Dependent variable	PU → BI PEoU → BI	(Cidral et al., 2018; Davis, 1989)

3. Research Model and Hypotheses

This study extends the Technology Acceptance Model (TAM) by incorporating two external variables, habit and self-efficacy, to investigate students' acceptance of Map-OLS. Building on previous theoretical and empirical research, the proposed model aims to examine the relationships among perceived usefulness (PU), perceived ease of use (PEoU), self-efficacy (SE), habit (HA), and behavioural intention (BI) in the context of map-based online learning systems. The research model proposed in this study is shown in Figure 1.

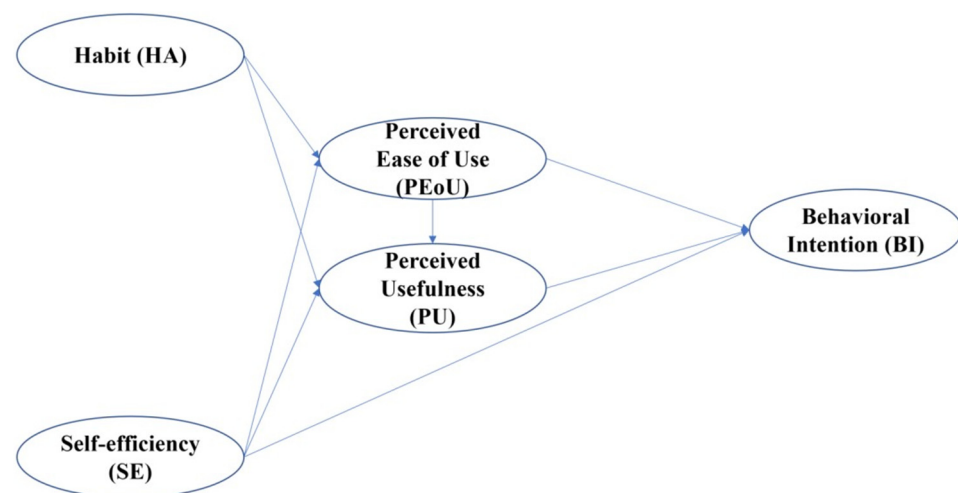


Figure 1. Research model. Each arrow represents a hypothesized positive relationship derived from theory, and these relationships are described in detail in the following subsections.

3.1. Habit

Limayem et al. (2007) defined habit in terms of the degree to which humans tend to automate behaviours as a result of learning and repetition. In information systems research, habit has been recognized as a strong predictor of usage behaviour and intention

(Amoroso & Lim, 2017). The extended UTAUT2 considered habit to be an indicator of usage intentions concerning information systems (Venkatesh et al., 2012). In online learning contexts, students who frequently engage with digital maps or similar interfaces may develop habitual behaviours that influence their perceptions of the system's ease of use and usefulness (Jeyaraj, 2022). Therefore, the following assumptions are put forward:

H1. *Habit positively affects the perceived ease of use (PEoU) of Map-OLS.*

H1a. *Habit positively affects the perceived usefulness (PU) of Map-OLS.*

3.2. Self-Efficacy

Bandura (2001) claimed that self-efficacy means that individuals think they can succeed or accomplish specific tasks under certain circumstances. Venkatesh (2000) proposed that self-efficacy, as a system-independent anchoring construct, plays a key role in shaping the PEoU of a new system. For example, some related studies have reported that learners who are more confident regarding their computer skills are more motivated to learn and more likely to complete tasks (Chen, 2014). In academic situations, learners who exhibit strong self-efficacy are more highly motivated to learn so as to achieve greater academic achievement because those learners believe that they are capable of achieving their goals (Yokoyama, 2019); on the contrary, learners with a relatively weak sense of self-efficacy are more likely to adopt ways that hinder the achievement of learning goals (Hanham et al., 2021). Based on previous research, this study proposed the following hypotheses:

H2. *Self-efficacy positively affects the perceived ease of use (PEoU) of Map-OLS.*

H2a. *Self-efficacy positively affects the perceived usefulness (PU) of Map-OLS.*

H2b. *Self-efficacy positively affects the behavioural intention to use Map-OLS.*

3.3. Perceived Ease of Use (PEoU)

PEoU is defined as the "degree to which a person thinks that it is effortless to use a particular system" (Davis, 1989). According to TAM, PU is influenced by PEoU because the easier a technology is to use, the more useful an individual will find it (Venkatesh, 2000). Venkatesh and Davis (2000) proposed that PEoU is a cognitive determinant of PU; that is, people form PU partly by cognitive comparison to judge whether a new system or technology can easily do what they need. Several studies have demonstrated that PEoU directly affects PU (Mohammadi, 2015). Moreover, according to TAM, the perception that a technology is easy to use influences users' behavioural intentions towards that technology (Arbaugh, 2000). Therefore, on the basis of previous research, this study proposed the following assumptions:

H3. *Perceived ease of use (PEoU) positively affects the PU of Map-OLS.*

H3a. *Perceived ease of use (PEoU) positively affects the behavioural intention to use Map-OLS.*

3.4. Perceived Usefulness (PU)

Davis (1989) believed that PU means that individuals think that the use of a specific system will improve their performance. Individuals' perception of a specific information system's usefulness determines their willingness to use it (Hanafizadeh et al., 2014). According to TAM, PU is one of the most critical predictors of behavioural intention to use technology or systems (Arbaugh, 2000). Some studies have reported that PU will determine the intention to use systems related to online learning (C.-T. Chang et al., 2017; Tarhini

et al., 2017; Wu & Chen, 2017). Hence, on the basis of previous research, the current study proposed the following hypothesis:

H4. *Perceived usefulness (PU) positively affects the behavioural intention to use Map-OLS.*

3.5. Behavioural Intention (BI)

According to TAM, behavioural intention is an important indicator to predict whether an individual is willing to use new systems and new technologies (Davis et al., 1989). In the domain of acceptance, some researchers have explored the relationship between behavioural intention and actual use in online learning (Chow et al., 2012; Hassanzadeh et al., 2012). To reduce complexity, Petter et al. (2008) proposed an updated model of information system success that does not distinguish between behavioural intention and actual use. Moreover, previous studies have reported that PEOU and PU are significantly and directly associated with usage intention rather than actual usage behaviour (Rafique et al., 2020). Therefore, this study employs behavioural intention as the outcome variable in the model.

In summary, this research model investigates how learners' prior behaviours (habit), perceived capabilities (self-efficacy), and cognitive evaluations (PU and PEOU) jointly influence their behavioural intention to adopt Map-OLS. By extending TAM with theoretically grounded constructs, the model aims to provide a more comprehensive understanding of the technology acceptance model in visually structured online learning environments.

4. Methods

4.1. Participants

To ensure the representativeness and reliability of the data, this study employed a random sampling method to recruit participants from a university in Central China. Prior to data collection, participants were provided with detailed information regarding the study's purpose, procedures, and their rights, and written informed consent was obtained. A total of 846 participants voluntarily participated in the survey. To ensure data quality, a lie detection item was included in the questionnaire; 34 respondents who failed this validity check were excluded from the final analysis, resulting in 812 valid responses.

All participants had prior exposure to or experience with the Map-based Online Learning System (Map-OLS) during their coursework or through institutional training activities. This ensured that participants possessed sufficient familiarity with the system to evaluate its perceived usefulness and ease of use in a meaningful manner. The final sample size significantly exceeded the minimum threshold of 150 participants, which is ten times the number of observed variables, thereby meeting the recommended criteria for structural equation modelling (Nunnally, 1967). Detailed demographic and background information of the participants is presented in Table 2.

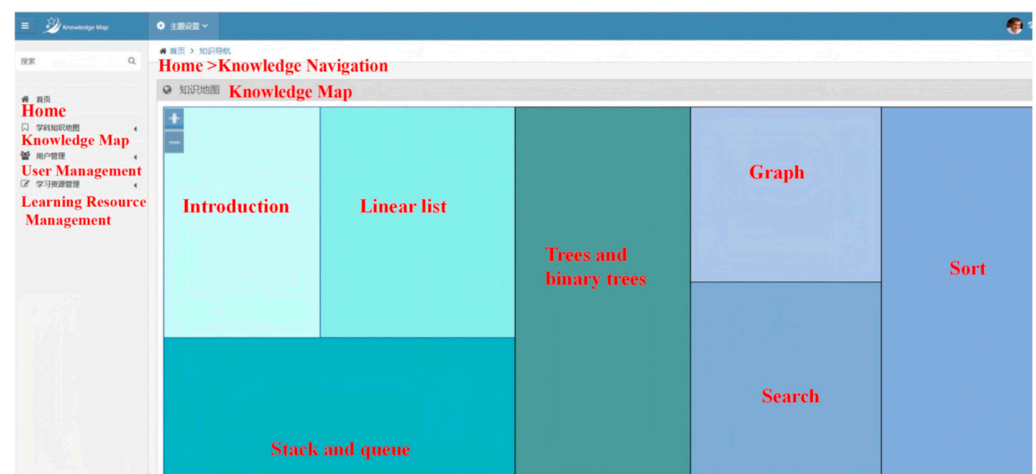
Table 2. Profile of respondents.

Variables	Classification	Frequency	Percentage
Gender	Male	444	54.7%
	Female	368	45.3%
Level of education	Undergraduate	501	61.7%
	Master's student	264	32.5%
	Doctoral student	47	5.8%
Online learning frequency	Every day	186	22.9%
	Two to three times per week	394	48.5%
	Two to three times per month	112	13.8%
	less than once a month	120	14.8%

Note: N = 812.

4.2. Procedure

The purpose of this study was to investigate learners' behavioural intention to use Map-OLS. In this study, we developed a prototype system, Map-OLS (see Figure 2). The system utilizes Data Structure, one of the fundamental courses in computer science, to construct the subject knowledge map as an example. Learners use the platform to engage in self-directed learning and can view different levels of learning resources by zooming in and out. When learners click on the quick sort button, for example, different types of learning resources appear, such as PPT courseware, videos, practice questions, and GitHub code. Learners then select one of the learning resources that meets their needs in accordance with their preferences regarding the types of learning resources available. In detail, Graphic (A) shows the response when a student logs into the system, and the map locates the knowledge unit that the student is to learn; Graphic (B) illustrates the result of clicking on the map, which provides the user with the new resource; and Graphic (C) illustrates a new window that opens to display the resource for the user (see Figure 3). During the actual data collection process, first, the functions and features of Map-OLS were introduced. Subsequently, the participants completed the questionnaire.

**Figure 2.** A screenshot of the map-based online learning interface.

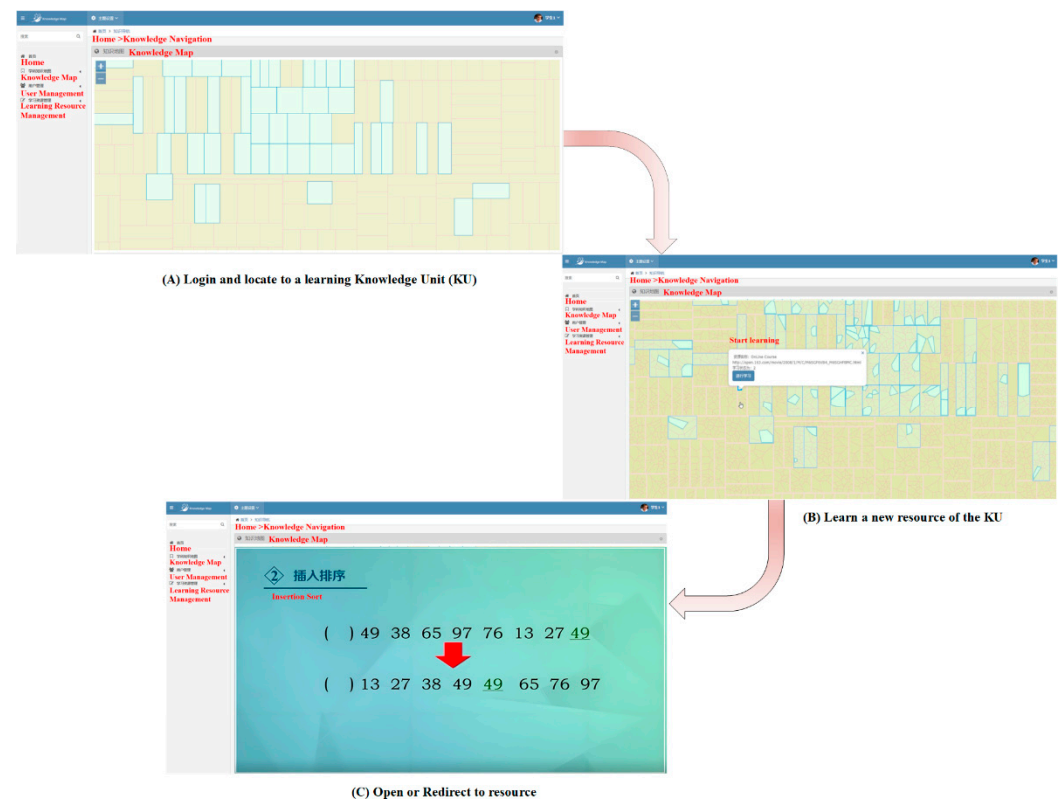


Figure 3. Actual learning process. (A) The last screenshot of the prior study after logging in. (B) Select one resource of the knowledge unit by clicking one polygon of the map to study. (C) Open the resource.

4.3. Instrument

All the data in this study were collected via an online testing platform (<https://www.wjx.cn/>, accessed on 1 October 2024). The questionnaire contained three sections. The first part introduced the functions and features of Map-OLS. The second section collected demographic information, such as gender, age, and the frequency of learners' use of existing online learning platforms. The third section consisted of 16 items that were scored on a Likert-type scale, with responses ranging from "1" (strongly disagree) to "7" (strongly agree); in this group, one item was a lie detector question, that is, "Please choose completely disagree from the following options". Three items adapted from Rafique et al. (2020) and Venkatesh et al. (2012) were used to measure habit. Three items adapted from (Abdullah & Ward, 2016) were used to measure self-efficacy. The items used to measure PEoU (n = 3 items), PU (n = 3 items), and behavioural intention (n = 3 items) were adapted from (Davis, 1989). We used the translation and back-translation methods to translate the items into Chinese (A. M. Chang et al., 1999). The questionnaire items are presented in Appendix A.

4.4. Data Analysis

To empirically test the research model and hypotheses, this study adopted a structural equation modelling (SEM) approach, as it enables the assessment of both the measurement model (validity and reliability of constructs) and the structural model (hypothesized relationships between latent variables) simultaneously. SEM was implemented using IBM SPSS version 20 for preliminary analysis and Mplus version 8.3 for model testing.

Data analysis was conducted in three main stages: (1) descriptive statistics, including multicollinearity diagnostics based on variance inflation factor (VIF) to confirm the absence of multicollinearity among predictors, and the mean and standard deviation of each latent

construct, were reported; (2) validation of the measurement model through confirmatory factor analysis (CFA); and (3) evaluation of the structural model to test the hypothesized paths. The maximum likelihood estimation (MLE) method was employed to estimate model parameters.

Model fit was evaluated using a combination of absolute and incremental fit indices, the Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) (Steiger, 1990). Following Hu and Bentler (1999), a CFI and TLI value above 0.90 indicates an acceptable model fit, while values above 0.95 are considered excellent. An RMSEA value below 0.08 and an SRMR value below 0.05 indicate a good model fit (MacCallum et al., 1996). These indices, combined with hypothesis testing for the model paths, allow for a comprehensive evaluation of the research model and its theoretical assumptions.

5. Results

5.1. Descriptive Analysis

To ensure the robustness of the structural equation modelling (SEM) results and mitigate estimation bias stemming from multicollinearity among independent variables, a diagnostic assessment for multicollinearity was conducted before interpreting the model. Following established guidelines (Hair, 2009), we computed the variance inflation factor (VIF) and Tolerance values for each predictor. Typically, VIF values below 10 and Tolerance values above 0.1 are deemed acceptable, indicating the absence of severe multicollinearity. Table 3 displays VIF values for habit (1.27), self-efficacy (2.79), perceived ease of use (3.13), and perceived usefulness (2.97), all falling within acceptable thresholds, suggesting insignificant multicollinearity concerns in this study. Tolerance values ranged from 0.32 to 0.79, further affirming the reliability of the model estimation.

Table 3. Multicollinearity diagnostics for independent variables.

Independent Variable	Tolerance	VIF
Habit (HA)	0.79	1.27
Self-efficacy (SE)	0.36	2.79
Perceived ease of use (PEoU)	0.32	3.13
Perceived usefulness (PU)	0.34	2.97

To assess the assumption of multivariate normality, descriptive statistics, including means, standard deviations, skewness, and kurtosis, were calculated for each construct (see Table 4). The results showed that the means ranged from 5.65 to 6.08, the standard deviations ranged from 0.72 to 0.92, the skewness ranged from -1.27 to -0.64 , and the kurtosis ranged from 0.50 to 2.99. According to the criteria recommended by Kline (2015), skewness values below 2 and kurtosis values below 7 indicate an acceptable level of univariate normality. Therefore, the data in this study satisfy the assumption of approximate multivariate normality required for structural equation modelling.

Table 4. Descriptive data of constructs measured.

Constructs	Number of Items	Mean	Std. Deviation	Skewness	Kurtosis
Habit (HA)	3	6.08	0.72	-1.27	2.99
Self-efficacy (SE)	3	5.65	0.89	-0.64	0.76
Perceived ease of use (PEoU)	3	5.70	0.92	-1.07	2.69
Perceived usefulness (PU)	3	5.69	0.85	-0.66	0.87
Behavioural intention (BI)	3	5.68	0.92	-0.65	0.50

Note: N = 812.

In addition, we explored whether participants' behavioural intention (BI) to use Map-OLS varied based on their frequency of engaging in online learning. Participants were grouped into four categories based on their reported online learning frequency: every day, two to three times per week, two to three times per month, and less than once a month. As shown in Table 5, the average BI score was highest among daily users ($M = 5.95$, $SD = 0.96$), followed by weekly users ($M = 5.69$, $SD = 0.85$), and lowest among those who engaged less than once a month ($M = 5.38$, $SD = 0.96$).

Table 5. ANOVA of behavioural intention to use Map-OLS by online learning frequency.

Online Learning Frequency	N	Behavioural Intention		F	p
		Mean	Std. Deviation		
Every day	186	5.95	0.96	9.72	<0.001
Two to three times per week	394	5.69	0.88		
Two to three times per month	112	5.70	0.85		
less than once a month	120	5.38	0.96		

A one-way ANOVA was conducted to examine whether there were statistically significant differences in BI among the four groups. The results indicated a significant main effect of online learning frequency on BI, $F(3, 808) = 9.72$, $p < 0.001$, as shown in Table 5. This suggests that students who engage more frequently in online learning tend to have significantly higher behavioural intentions to use Map-OLS.

5.2. Analysis of Measurement Model

Before analyzing the structural model and testing the research hypothesis, the goodness-of-fit index of the model was calculated by using the Mplus version 8.3 software. Table 6 shows that the measurement model fits relatively well with the collected data ($CFI = 0.97$, $SRMR = 0.026$, $RMSEA = 0.056$). Moreover, Table 7 shows that all factor loadings range from 0.70 to 0.82, which is much higher than 0.30; thus, good convergent validity is indicated (Hair, 2009). In general, convergent validity was tested using the average variance extracted (AVE), and composite reliability (CR) was used to assess reliability. According to Fornell and Larcker (1981), an AVE greater than 0.50 indicates that convergent validity is good. If the CR value is equal to or greater than 0.5, the reliability is sufficient (Fornell & Larcker, 1981). Table 7 indicates that AVE and CR scores in this study are acceptable.

Discriminant validity was assessed using the Fornell–Larcker criterion, which stipulates that the square root of the average variance extracted (AVE) for each construct should exceed its squared correlations with any other construct (Fornell & Larcker, 1981). As shown in Table 8, the results indicate that most constructs met the Fornell–Larcker criterion, confirming adequate discriminant validity. Nonetheless, two exceptions emerged. First, the AVE for PU (0.56) was lower than its squared correlation with PEOU (0.63). Second, the AVE for BI (0.58) was slightly lower than its squared correlation with PU (0.60). These results suggest some degree of conceptual overlap among these constructs. Such overlap is not unexpected, as previous research has consistently demonstrated a strong empirical and theoretical association between PEOU and PU (Davis, 1989; Venkatesh & Davis, 2000). In the context of technology acceptance, particularly in self-directed online learning environments, learners who find a system easy to use are also more likely to perceive it as useful, leading to higher correlations. Similarly, learners who believe a system is useful often develop stronger intentions to use it, which may explain the elevated correlation between PU and BI. Although these findings are theoretically justifiable within the TAM framework, the results call for careful interpretation. Future studies may consider refining the measurement

instruments to reduce conceptual redundancy or applying alternative methods, such as the Heterotrait–Monotrait (HTMT) ratio, to further validate discriminant validity.

Table 6. Fit indices of measurement model.

Model Goodness-of-Fit Indices	Recommended Level of the Fit	Measurement Model
χ^2	Not significant	266.56
χ^2/df	<5	3.51
CFI	>0.90	0.97
TLI	>0.90	0.96
RMSEA	<0.08	0.056
SRMR	<0.05	0.026

Note: N = 812.

Table 7. Construct reliability and convergent validity.

Constructs	Items	Standardized Factor Loadings	Cronbach's Alpha	AVE	Composite Reliability
HA	HA1	0.73	0.77	0.52	0.77
	HA2	0.74			
	HA3	0.70			
SE	SE1	0.73	0.81	0.57	0.80
	SE2	0.77			
	SE3	0.77			
PEoU	PEoU1	0.78	0.84	0.64	0.84
	PEoU2	0.82			
	PEoU3	0.79			
PU	PU1	0.77	0.79	0.56	0.79
	PU2	0.72			
	PU3	0.76			
BI	BI1	0.77	0.80	0.58	0.80
	BI2	0.78			
	BI3	0.73			

Table 8. Discriminant validity.

Constructs	1	2	3	4	5
1. HA	0.52				
2. SE	0.19	0.57			
3. PEoU	0.25	0.50	0.64		
4. PU	0.23	0.52	0.63	0.56	
5. BI	0.21	0.56	0.61	0.60	0.58

Note: Diagonal values in bold represent the square roots of AVE for each construct. Discriminant validity is established when these values are greater than the corresponding inter-construct correlations.

5.3. Analysis of Structural Model

The hypothesized relationships described in our initial model (see Figure 1) were tested collectively using structural equation modelling (SEM) via Mplus. The SEM test results are shown in Figure 4 and Table 9. As shown in Figure 4, eight hypotheses were tested and confirmed. The specific hypothesis testing results are presented in Table 9, including β coefficients, t-values, and whether the hypotheses hold. The results indicated the significant acceptance of all the factors with respect to behavioural intention to use Map-OLS. Specifically, habit directly influences PEoU and PU (H1: $\beta = 0.23$, $p < 0.001$; H1a: $\beta = 0.07$, $p < 0.01$). Self-efficacy positively influences PEoU, PU, and behavioural intention to use Map-OLS (H2: $\beta = 0.61$, $p < 0.001$; H2a: $\beta = 0.30$, $p < 0.001$; H2b: $\beta = 0.32$, $p < 0.001$). Furthermore, PEoU significantly affects PU and behavioural intention to use Map-OLS (H3: $\beta = 0.55$, $p < 0.001$; H3a: $\beta = 0.30$, $p < 0.001$). PU has a significant positive influence on behavioural intention to use Map-OLS (H4: $\beta = 0.32$, $p < 0.001$).

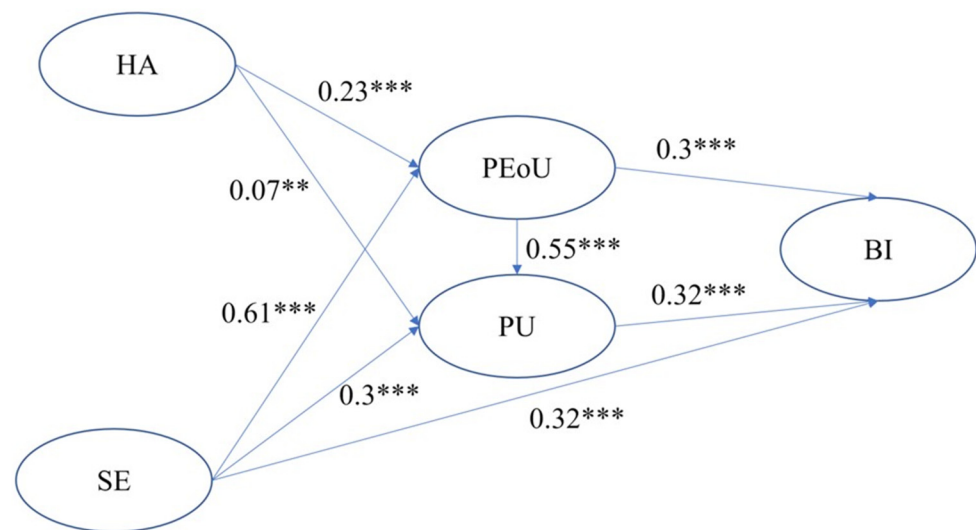


Figure 4. Path analysis. The figure shows the tested relationships among the variables in the extended TAM. All path coefficients (β) are significant, indicating that habit and self-efficacy positively influence PEOU and PU, which in turn affect behavioural intention to use Map-OLS. Note: ** $p < 0.01$, *** $p < 0.001$.

Table 9. Hypothesis testing.

Hypothesis	β Coefficients	t Values	Status
H1: HA $\rightarrow$ PEOU	0.23 ***	8.75	Supported
H1a: HA $\rightarrow$ PU	0.07 **	3.16	Supported
H2: SE $\rightarrow$ PEOU	0.61 ***	27.49	Supported
H2a: SE $\rightarrow$ PU	0.30 ***	10.87	Supported
H2b: SE $\rightarrow$ BI	0.32 ***	11.19	Supported
H3: PEOU $\rightarrow$ PU	0.55 ***	19.89	Supported
H3a: PEOU $\rightarrow$ BI	0.30 ***	9.34	Supported
H4: PU $\rightarrow$ BI	0.32 ***	9.63	Supported

Note: ** significance at $p < 0.01$; *** significance at $p < 0.001$.

To further evaluate the relative contributions of each predictor to behavioural intention, Cohen's f^2 effect sizes were calculated in accordance with established guidelines (Cohen, 2013). According to these guidelines, an f^2 value of 0.02 indicates a small effect, 0.15 represents a medium effect, and 0.35 denotes a large effect. As presented in Table 10, habit demonstrated a medium effect size ($f^2 = 0.19$), indicating a substantial influence on learners' behavioural intention to use the system. Perceived ease of use ($f^2 = 0.15$) also approached the threshold for a medium effect, suggesting a notable role in shaping user intentions. In contrast, both self-efficacy ($f^2 = 0.04$) and perceived usefulness ($f^2 = 0.06$) exhibited small effect sizes, reflecting more limited contributions. These findings underscore the comparatively stronger predictive power of habitual behaviours and usability perceptions over individual confidence and perceived utility in the context of technology adoption for map-based online learning systems.

Table 10. Cohen's f^2 effect sizes for predictors of behavioural intention.

Predictor Variable	R^2 (Reduced)	f^2	Effect Size Interpretation
Habit (HA)	0.66	0.19	Medium
Self-efficacy (SE)	0.70	0.04	Small
Perceived ease of use (PEoU)	0.67	0.15	Medium
Perceived usefulness (PU)	0.70	0.06	Small

6. Discussion

This paper examined learners' acceptance of using Map-OLS and the factors influencing their behavioural intentions to use the system, such as habit and self-efficacy. The results confirmed that PEOU and PU are significant direct predictors of the behavioural intention to use Map-OLS, while habit and self-efficacy are the factors that affect the behavioural intention to use Map-OLS. Self-efficacy also directly influenced the behavioural intention to use Map-OLS. These findings provide empirical support for extending TAM with psychological constructs and offer practical insights for enhancing the design and adoption of online learning systems, such as Map-OLS.

As hypothesized, habit had a significant positive impact on both PEOU and PU. This finding is consistent with previous studies indicating that habitual behaviours, particularly those involving frequent interaction with digital maps or related tools, could reduce cognitive load and increase perceived system usability (Rafique et al., 2020). Specifically, repeated engagements with an e-map or e-map-related applications could help establish certain intentions, which in turn influence PEOU and PU (Jeyaraj, 2022). These results support the inclusion of habit as a relevant external variable in TAM, as previously suggested by Venkatesh et al. (2012). In the context of Map-OLS, students with habitual use of digital maps (e.g., Google Maps) were more likely to perceive the system as intuitive, useful, and easy to use, thereby enhancing their behavioural intention to adopt it.

The results also confirmed that self-efficacy positively influences PEOU, PU, and behavioural intention. This underscores the importance of learners' confidence in their ability to navigate and utilize online learning technologies, especially in self-directed environments with limited instructor guidance (Mun & Hwang, 2003; Venkatesh, 2000). Students who reported higher self-efficacy were more likely to find Map-OLS both easy to use and useful and to express a stronger intention to use the system. These findings extend previous research by linking motivational factors from social psychology to TAM constructs, highlighting the importance of designing systems that foster user confidence and autonomy.

As is consistent with prior research, PEOU was found to significantly affect both PU and behavioural intention. This finding reveals that PEOU influences behavioural intention to use Map-OLS not only directly but also indirectly via PU. Evidently, the easier it is for students to use Map-OLS, the more likely students are to perceive it as useful and the more willing they are to use it. Similar conclusions were found in previous studies (Rafique et al., 2020; Wu & Chen, 2017). The results provided a solid foundation for TAM and also proved once again that PEOU, PU, and behavioural intentions are the core variables of TAM (Davis, 1989).

The analysis also showed that PU significantly influences behavioural intention, indicating that students are more inclined to adopt Map-OLS when they perceive it as beneficial to their learning. As a visual tool for organizing and retrieving learning resources, Map-OLS enables learners to access knowledge more efficiently, thereby enhancing its perceived usefulness. This result is in line with the conclusions of previous studies that have shown that PU significantly influences usage intention with respect to online learning systems (Mohammadi, 2015).

While our results reinforce established TAM relationships, prior studies have reported mixed findings. For instance, Barz et al. (2024) found that digital self-efficacy did not significantly influence PU or PEOU among German university students. Similarly, Isaac et al. (2017) reported that internet self-efficacy had only marginal effects on PU and moderate effects on PEOU among Yemeni government employees. Park (2009) also noted that PU may not always significantly predict behavioural intention in e-learning environments, particularly when learners lack prior exposure. These inconsistencies underscore that

TAM relationships are often context-dependent. In our study, the exploratory interface of Map-OLS and learners' familiarity with digital maps may have amplified the effects of habit and self-efficacy, suggesting that user background and system characteristics remain critical factors for future research.

To further explore contextual factors, we conducted an additional analysis to explore whether the frequency of learners' engagement with online learning activities is associated with their intention to adopt Map-OLS. The results indicated that students with more frequent online learning experiences tended to show stronger adoption intentions. This trend suggests that familiarity with digital learning environments may positively shape users' openness to adopting novel systems such as Map-OLS. These insights reinforce the argument that experiential factors, such as prior system use and habit, can play a critical role in shaping learners' technology acceptance (Teo, 2011; Venkatesh et al., 2003). Future implementations of map-based systems may, therefore, benefit from targeted interventions that build learners' digital learning experience and comfort prior to adoption.

In conclusion, this study proposed and validated an extended TAM to explain learners' behavioural intentions to use Map-OLS. Both habit and self-efficacy were confirmed as important external variables influencing PEOU, PU, and, ultimately, behavioural intention. These results contribute to the literature by demonstrating the value of integrating psychological constructs into TAM, especially in the context of interactive learning environments. As map-based systems become increasingly common in personalized learning, understanding how learner characteristics interact with system features will be essential for promoting widespread adoption and effective use.

Implications and Limitations

This paper has two theoretical implications since it contributes to our knowledge of both the role of maps as important learning tools for enhancing engagement and the broader applicability of the TAM framework. First, this study applied maps to online learning and implemented a customized prototype of a map-based online learning system, which used maps to organize and manage online learning resources and to support learners in engaging in map-based learning interactions. The findings showed that both PEOU and PU had direct positive effects on the behavioural intention to use Map-OLS. This further indicated that maps are effective teaching tools, suggesting that this map-based online learning system could stimulate students' learning interests and enhance their engagement in online learning. Second, this study advances the theoretical application of TAM by extending it with habit and self-efficacy, demonstrating its relevance in the context of map-based online learning systems. The results of the hypothesis testing supported the proposed significant correlations among TAM constructs referenced in this paper. This study greatly expands our understanding of the factors that affect user acceptance of Map-OLS.

The practical implications of this study provide concrete guidance for both educators and developers in designing and optimizing map-based online learning environments. On the one hand, the implementation of Map-OLS demonstrates that leveraging digital map interfaces can address persistent challenges in online learning—such as low engagement and high dropout rates—by promoting intuitive navigation and learner-centred content interaction. Educators can apply these insights by restructuring instructional strategies. For instance, they may organize learning tasks as map nodes that allow students to select content based on personal interests and progress, thereby enhancing learner autonomy and intrinsic motivation. On the other hand, individual-related factors also play a role in learners' willingness to use Map-OLS. When designing an online learning system, user-friendliness and ease of use should be taken into consideration. If a system is easy to

navigate, rich in content, and functionally well-designed, it can improve satisfaction and increase the utilization of online learning systems (Cidral et al., 2018).

Although it is rigorous and comprehensive, this study still has some limitations. First, this study considered only the effects of two external variables, i.e., self-efficacy and habit, on the two determinants of PEOU and PU. It may be the case that more than two factors influence those two key determinants. Future studies should check whether it is possible to include other external variables that have not been explored in this study. Second, this study only measured perceptions and intentions to use Map-OLS at a single point in time. It is worth noting that students' PEOU and PU of Map-OLS change over time. Accordingly, longitudinal studies should be conducted to evaluate the effectiveness of the model proposed in this study, taking into account the changes in user perception and behavioural intention over time. Third, the data collected in this study were obtained from a subjective questionnaire used to evaluate learners' willingness to use Map-OLS. In the future, additional physiological indicators, such as eye movement indicators, can be considered to evaluate the usefulness of the system. Despite its limitations, this study is valuable since it has several important insights for educators and developers of Map-OLS.

7. Conclusions

This study examined the factors influencing learners' acceptance of a map-based online learning system (Map-OLS) by extending the Technology Acceptance Model (TAM) to incorporate two theoretically grounded constructs: habit and self-efficacy. The findings confirmed that all proposed hypotheses were supported. Specifically, both habit and self-efficacy exerted significant positive effects on PEOU and PU, indicating that students with more habitual engagement with maps and stronger beliefs in their abilities are more likely to perceive Map-OLS as easy to use and useful. Additionally, PEOU positively influenced PU and behavioural intention, confirming the core assumptions of TAM. Furthermore, PU and self-efficacy both directly and positively affected students' behavioural intention to use Map-OLS. These findings demonstrate that the extended TAM effectively captures the psychological and experiential factors that drive learners' acceptance of visually structured online learning systems. Compared to prior studies applying TAM in online learning contexts (Chahal & Rani, 2022; Luo & Du, 2022), this study offers a novel perspective by focusing on a map-based system and incorporating constructs that reflect user habits and confidence.

Author Contributions: Conceptualization, W.X. and D.Z.; methodology, W.X.; software, C.W. (Chaodong Wen); validation, W.X., C.W. (Chunli Wang) and C.W. (Chaodong Wen); formal analysis, W.X.; investigation, W.X.; resources, K.Z.; data curation, C.W. (Chaodong Wen); writing—original draft preparation, W.X.; writing—review and editing, W.X.; visualization, C.W. (Chunli Wang); supervision, D.Z.; project administration, D.Z.; funding acquisition, K.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China under grant number [62477008]; the 2022 Annual Program for Innovative Research Teams in Science and Technology of Henan Province Universities, "Big Data Analysis and Application in Education", under grant number [22IRTSTHN031]; the Research Planning Project for Humanities and Social Sciences by the Ministry of Education of China under grant number [24YJA880016]; and the Doctoral Research Initiation Funds from Henan Normal University. This article is a result of a major scientific research project supported by the Henan Provincial Collaborative Innovation Center for Intelligent Education.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Henan Normal University Ethics Committee (protocol code: HNSD-2025BS.0102; date of approval: 26 October 2024).

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

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Constructs	Items	Measures	References
Habits	HA1	Using the electronic map via the mobile internet has become a habit for me.	(Rafique et al., 2020; Venkatesh et al., 2012)
	HA2	I can no longer travel without electronic maps (such as Baidu Maps, Google Maps, etc.).	
	HA3	Using the electronic map via my smartphone has become natural for me.	
Self-Efficacy	SE1	I am confident using the map-based online learning system even if there is no one around to show me how to do it.	(Abdullah & Ward, 2016)
	SE2	I am confident using the map-based online learning system even if I have never used such a system before.	
	SE3	I am confident using the map-based online learning system even if I only have the system manual for reference.	
Perceived Ease of Use	PEoU1	The map-based learning system presents knowledge and learning resources visually, so it is easy for me to find the learning resources I need.	(Davis, 1989)
	PEoU2	My interaction with the map-based online learning system is clear and understandable.	
	PEoU3	I often use Baidu Maps and other electronic maps in my daily life for positioning, navigating and searching locations, which make it easy for me to use the map-based online learning system to learn.	
Perceived Usefulness	PU1	Using the map-based online learning system allows me to accomplish learning tasks more quickly.	(Davis, 1989)
	PU2	I find the map-based online learning system useful in my learning.	
	PU3	Using the map-based online learning system enhances my learning effectiveness.	
Behavioural Intention	BI1	I intend to continue using the map-based online learning system during my study period.	(Davis, 1989)
	BI2	Given access to the map-based online learning system, I predict that I would use it.	
	BI3	I plan to use the map-based online learning system in the future.	

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