An Investigation of the Factors Influencing Behavioral Intentions in Self-Directed Online Learning by Integrating the Task-Technology Fit and Technology Acceptance Models

CHENG-CHE LIN[1], HAO-TE LU[2], YI-CHOU WANG[3*]
[1,3]Department of International Business Management, Tainan University of Technology, No.529, Zhongzheng Rd., Yongkang District, Tainan City 710302,
TAIWAN (R.O.C.)

[2]Department of Finance, Tainan University of Technology, No.529, Zhongzheng Rd., Yongkang District, Tainan City 710302,
TAIWAN (R.O.C.)

Corresponding Author

Abstract: - Online learning, a popular form of self-directed learning, relies on interactive and cooperative frameworks to provide students with educational opportunities. The results of the study show that TTF and computer self-efficacy have a positive impact on the perceived usefulness (PU) and perceived ease of use (PEU) of self-directed online learning. Additionally, PU and PEU played a mediating role in the relationship between TTF and behavioural intention. The findings emphasize the importance of cross-disciplinary knowledge acquisition through online self-learning as a motivator for students.

Key-Words: - online learning environments, self-directed learning, task-technology fit, technology acceptance model, FinTech learning resources, Computer self-efficacy.

Received: August 29, 2025. Revised: December 24, 2025. Accepted: February 26, 2026. Published: June 16, 2026.

1 Introduction

The outbreak of COVID-19 posed an unprecedented global disruption that fundamentally compromised students' well-being and educational continuity, compelling institutions worldwide to accelerate the transition toward online learning as a sustainable alternative to conventional face-to-face instruction. In response, educational institutions and content providers have substantially redirected resources toward the development and expansion of e-learning infrastructures, drawing upon recent advancements in internet technologies to ensure uninterrupted access to quality education, [1], [2]. Online learning, a derivative of self-directed learning, has replaced the project-based notion of independent formats, fostering highly interactive and collaborative educational environments, [3]. Studies have shown that self-directed learning increases students' confidence in independent learning, [4], [5]. Previously, research on the effects of science and technology on learning behavior primarily focused on cognitive theory, [6], [7], [8], and attitude theories, [9], [10]. The present study integrated these two research orientations to clarify how modern technology affects behavioral cognition and attitudes about online self-directed learning.

Previous studies have frequently employed the Technology Acceptance Model (TAM) to explore users' behavioral intentions, [7], [11]. The task-technology fit (TTF) theory has gained prominence, and scholars are increasingly integrating the TTF model (TTFM) and TAM to delve into behaviors and tendencies related to internet use, [12], [13], [14], [15]. Thus, the present study aims to integrate the TAM and TTFM to examine the factors influencing behavioral intentions to use FinTech-based online resources for self-directed online learning. The potential impact of our findings on the future of online learning is significant, and we hope that our research will contribute to the continued evolution and improvement of this field.

2 Methodology Section

2.1 Self-directed Learning

Self-directed learning (SDL) has garnered considerable attention as a transformative pedagogical approach that repositions learners as active agents in their own educational development, cultivating a strong sense of autonomy, independence, and personal accountability. Beyond promoting self-governance, SDL systematically nurtures a constellation of higher-order competencies — including critical thinking, problem-solving, self-assessment, and adaptability — that are increasingly recognized as indispensable across both academic and professional domains, [2], [14], [16]. SDL is defined not by specific tools or platforms but by its emphasis on learner agency. SDL is characterized not by the medium through which learning occurs, but by the degree of agency exercised by the learner. Fundamentally, it encompasses a cyclical process in which individuals independently plan their learning objectives, execute the corresponding activities, and critically evaluate their own progress — all with limited reliance on external instruction, [17], [18]. Within SDL-oriented environments, educators undergo a fundamental role transformation — transitioning from primary knowledge transmitters to supportive facilitators who assist learners in articulating meaningful goals, locating appropriate resources, and engaging in critical reflection on their own progress. Empirical evidence consistently indicates that the adoption of personalized learning objectives, differentiated learning pathways, and structured reflective practices is positively associated with elevated levels of learner engagement, satisfaction, and academic achievement, [19].

Technology has quietly reshaped how SDL works in practice. With virtual classrooms, mobile learning apps, MOOCs, and learning management systems now widely available, students can access a broad range of content whenever and however they need it. This accessibility has steadily pushed SDL into digital territory, leading researchers to identify a distinct phenomenon they call self-directed online learning (SDOL). Studies exploring this area consistently find that learners who engage in SDOL tend to perform better and report more meaningful learning experiences, whether in school or at work, [1], [2], [20], [21]. In this study, SDL is operationalized as students' proactive engagement with FinTech-related online learning resources.

2.2 Behavioral Theory

What makes people decide to act — or not — has puzzled researchers in social psychology and information systems for decades. One of the earliest and most widely cited attempts to answer this question is the Theory of Reasoned Action (TRA), proposed by [22] At its core, TRA argues that before someone acts, two things shape their intention: whether they personally see the behavior as worthwhile, and whether the people they care about would approve of it. In other words, both personal judgment and social expectation play a hand in pushing someone toward — or away from — a given action. Recognizing the limitations of TRA in accounting for non-volitional behaviors, [23] extended the model by developing the Theory of Planned Behavior (TPB). TPB builds on this by adding a third element — how much control a person feels they actually have over the behavior. If something seems too difficult or out of reach, even the best intentions may not be enough to follow through, [24]. This extension enables TPB to better account for external constraints and facilitating conditions that may influence behavioral execution, thus enhancing its predictive utility, [25], [26], [27].

Drawing from these behavioral theories, [7] introduced the Technology Acceptance Model (TAM) to shed light on why people choose to use — or avoid — information technology. The model centers on two beliefs: whether a person thinks a technology will actually make their work easier, and whether they find it simple enough to use without much effort. Over the years, researchers across a wide range of fields have put TAM to the test and repeatedly found it holds up well in explaining technology adoption behavior, [28], [29], [30], [31], [32].

While TPB and TAM each started out as separate frameworks, researchers have since made a compelling case for combining them — arguing that what one model misses, the other tends to cover

[16], [33], [34], [35], [36]. Combining the two models gives researchers a more complete picture — one that accounts for how people think, what others expect of them, and how much control they feel they have, all at once. A good example of this overlap is how easily a technology can be used, which some scholars treat as a direct reflection of how much control a person perceives over their own behaviour [34]. While subjective norms have been linked to perceived usefulness, either as a moderating variable [34] or as a direct predictor.

Nevertheless, TAM's explanatory scope remains constrained; empirical evidence suggests that the model accounts for approximately 40% of the variance in system usage, leaving a considerable portion of user behavior unexplained, [37]. In response to the shortcomings observed when TAM and TPB are applied in isolation, researchers have advocated for incorporating the Task-Technology Fit (TTF) model originally proposed by as a means of strengthening the overall explanatory framework,

[15]. Central to TTF is the notion that a technology's value is contingent upon how well its capabilities align with the demands of the tasks it is meant to support.

Whereas TAM focuses on individual perceptions of a system's utility and usability, TTF shifts attention to whether the technology is genuinely suited to the tasks at hand. By combining these perspectives, the integrated model allows both researchers and practitioners to move beyond the question of adoption intent and examine whether a given technology can realistically support users' objectives and day-to-day workflows, [14].

2.3 Task-technology Fit Model

This integrated perspective holds particular relevance in technology-mediated learning contexts, where it is not sufficient for learners to simply view a system favorably — the technology must also prove capable of addressing their specific academic demands and learning objectives. The TTF model challenges the assumption that technology adoption is driven purely by user attitudes, arguing instead that what matters most is the degree to which a system's capabilities correspond to the functional demands of the tasks users are required to carry out. When this correspondence is strong, users are better positioned to complete tasks efficiently and productively. When it is weak, however, the mismatch tends to generate user frustration, diminished performance, and a failure to fully utilize the system's potential, [15].

At its core, TTF centers on the correspondence between what a technology offers and what a task actually requires. This alignment is shaped by multiple factors, including the nature and complexity of the tasks involved, the functional capabilities of the technology, and the proficiency of the users themselves. Beyond these individual-level considerations, organizational conditions — such as institutional backing and the accessibility of necessary resources — also play a meaningful role in determining how effectively technology can support task execution, [38], [39], [40], [41]. When a technology is deliberately structured to correspond with users' actual work or learning demands, it lowers cognitive load, creates space for experimentation, and fosters the emergence of innovative approaches to problem-solving, [15]. TTF is shaped by three broad categories of antecedents: characteristics of the task (such as complexity, structure, and interdependence), characteristics of the technology (such as usability, functionality, and reliability), and characteristics of the individual user (such as skill level, motivation, and prior experience).

Within the context of online self-directed learning, TTF reflects the extent to which digital tools — encompassing platforms, content resources, and interactive features — are capable of meaningfully supporting learners in pursuing their educational objectives. Where a strong correspondence exists between learning task demands and technological capabilities, learners tend to demonstrate higher levels of engagement, greater satisfaction with the learning experience, and more favorable academic outcomes, [42].

A critical antecedent of TTF in learning environments is the concept of flow experience, introduced by [43]. Flow denotes a psychological state in which individuals become deeply absorbed in an activity, experiencing a heightened sense of control, sustained attention, curiosity, and intrinsic motivation. Within online learning environments, the attainment of this state has been consistently associated with improved comprehension, stronger knowledge retention, and greater persistence in the face of challenges, [11], [44], [45].

Computer self-efficacy was derived from [46], [47] Social Cognitive Theory. It refers to individuals beliefs in their capabilities to perform computer-related tasks. [48] adapted this concept to the information systems (IS) domain, defining it as confidence in one's ability to apply computer skills in diverse settings. Importantly, computer self-efficacy represents a learner's perceived capability rather than their objectively measured skill level . Those who hold strong beliefs in their own technological competence are more inclined to approach online platforms with confidence, actively explore available functionalities, and sustain effort when difficulties arise. In contrast, learners with weaker self-efficacy beliefs are prone to heightened anxiety, diminished participation, and less favorable learning outcomes, [49], [50], [51].

Although TAM has proven to be a valuable model and explains approximately 40% of online usage, questions persist regarding behavioral intentions toward online learning resources [50], particularly due to variables associated with social change processes. In this study, flow experience, computer self-efficacy, and task-technology characteristics are identified as key antecedents of TTF in the online self-directed learning context.

When learners perceive strong alignment between their educational tasks and the functionalities of FinTech-based digital learning tools, they experience smoother, more engaging, and productive learning processes.

3 Research Methodology

3.1 Conceptual Model and Hypotheses

Figure 1 presents the the conceptual framework of **TTFM** employed in this study of college business administration students and their motivation for using FinTech as an online resource for self-directed learning. According to the model, behavioral intentions to adopt online FinTech resources depend on the enlightening integration of TTF-specific factors (task characteristics, individual flow experience, and computer self-efficacy) and TAM-specific factors (computer self-efficacy, PU, and PEU). Intention refers to the extent to which the user intends to use online FinTech resources in the future.

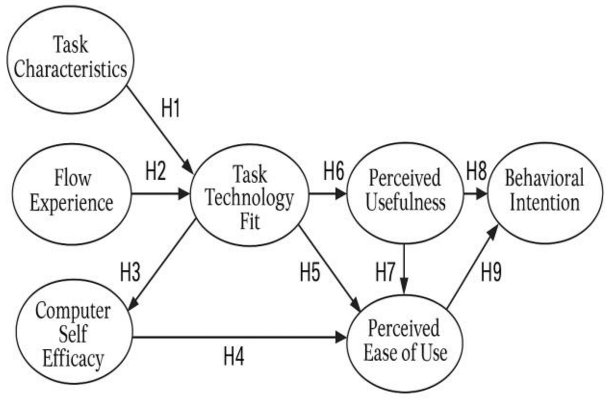

Fig. 1: Research model
Source: created by the authors

TAM focuses on the user's IT capabilities as opposed to the ability of IT to facilitate the user's self-learning. Thus, the TAM lacks the task attribute facet and how IT fits the task, so it cannot accurately represent IT evaluation results, [15]. If a research model can explicitly incorporate task characteristics, it can improve its interpretation of IT use, [14]. Thus, we integrated the two theories of TTF and the TAM to explain the variables responsible for the willingness of individuals to use an online self-directed learning system.

Task-technology fit model

According to this model, TTF involves three antecedents: task characteristics, personal flow experience, and computer self-efficacy. First, task characteristics refer to the characteristics that encourage users to rely on IS to perform tasks, such as fees, website evaluation, website update speed, and convenience, [52], [53], [54]. Previous studies have found that task characteristics (the socio-technical system, communications, web-based cooperative learning, problem-solving, etc.) positively affect TTF, [55], [56], [57]. Therefore, the following hypothesis is proposed:

H1: Task characteristics positively affect TTF for a self-directed learning student.

Second, flow experience has been studied and identified as a possible measure of online user experience, [58], [59], [60]. Previous research has revealed a positive relationship between flow experience and TTF [59], [61]. This leads to the second hypothesis:

H2: Individual flow experience positively affects TTF for a self-directed learning student.

Third, [47] explored whether an individual has a strong motivation for performing a particular task or action depending on the assessment of personal self-efficacy, as those with high self-efficacy tend to set higher goals. Some research has indicated that after engaging in a particular learning activity, a student will self-assess according to previously set goals, [62]. These processes directly affect the individual's self-efficacy and, in turn, the next encounter regarding the targets set for similar work. Previous studies of computer learning have demonstrated that self-efficacy has a direct effect on a learner's task characteristics and PEU, [7], [48], [63], [64], [65]. On this basis, the following hypotheses are proposed:

H3: Computer self-efficacy positively affects TTF for a self-directed learning student.

H4: Computer self-efficacy positively affects PEU for a self-directed learning student.

Technology acceptance model

[63] found that if the task characteristics and system characteristics are highly compatible, the user will find the system easy to use. [14] found that the suitability of TTF has a significant effect on the PEU. [15] found that PU is subjective for the user regarding specific IT to enhance performance and future benefits. For example, when performing a task activity, a user chooses an IT tool and assesses its usefulness in supporting the task. Previous studies have identified important antecedents of behavioral intention toward learning websites[37], [65], [66], [67], [68], [69], [70]. To this end, the following hypotheses are proposed:

H5: A student's perceived TTF positively affects the website's PEU for self-directed learning.

H6: A student's perceived TTF positively affects the PU of the website for self-directed learning.

H7: A student's PU positively affects the website's PEU for self-directed learning.

H8: A student's PU positively affects the student's behavioral intention of using the website for self-directed learning.

H9: A student's PEU positively affects the student's behavioral intention regarding the use of the website for self-directed learning.

3.2 Research Methodology

To explore students' behavioral intentions to retrieve FinTech resources from an online website program using self-directed learning, a survey was conducted during the second term of 2022, in which data were gathered from college business administration students representing 15 universities in Taiwan using a self-reported questionnaire. In total, 500 usable complete responses were obtained. As an incentive for participating, all students who completed the entire survey were offered a gift. The mean age of the respondents was 19.15 years (SD = .79): 215 (43%) were male and 285 (57%) were female. The mean difference between the top-scoring one-third (i.e., the top 166) and bottom-scoring one-third (bottom 166) of all respondents was assessed to test for non-response bias: no significant statistical differences were obtained with regard to the variables addressed in this research. The respective p-values were .32 for task characteristics, .51 for flow experience, .37 for computer self-efficacy, .39 for TTF, .61 for PU, .56 for PEU, and .52 for behavioral intention. To further validate the robustness of the sample, independent sample t-tests, one-way ANOVA, and chi-square tests were conducted. The t-test was employed to examine gender differences in perceived usefulness (PU), perceived ease of use (PEU), and behavioral intention (BI). The ANOVA tested whether there were significant variations in behavioral intention across different academic years, while the chi-square test assessed the relationship between prior online learning experience and behavioral intention.

To further validate the robustness of the sample and examine differences between groups, we conducted additional analyses. Independent samples t-tests showed no significant gender differences in PU and PEU (e.g., PU: $t = 0.98$, $p > .05$; PEU: $t = 1.24$, $p > .05$), although the BI was slightly higher for girls than for boys ($t = 2.13$, $p < .05$). Similarly, one-way variance analysis also found no significant difference in BI between grade groups ($F = 1.57$, $p > .05$). However, chi-square tests indicated a significant association between prior online learning experience and BI ($\chi^2 = 12.46$, $p < .01$). We have included these results in our analysis to present a more comprehensive statistical profile of the sample.

3.3 Research Model

Based on the literature and the context of this study, a research framework was developed in an attempt to identify the factors responsible for affecting the behavioral intention of self-directed learning in an online environment. The surveys were provided in traditional Chinese: all items included in the survey were compiled in English and then translated into Mandarin by translation/back-translation, [71]. The back-translation procedure was administered to ensure the equivalence of the scales. The instrument was validated using both a pre-test and a pilot test. The pre-test included 10 respondents who were experts in the field of online learning; they were asked to comment on the length of the instrument, the format, and the wording of the scales. Finally, after a pilot test involving 30 respondents, the survey was circulated among the population of online learning students.

For this study, the measure included six items, and Cronbach's alpha was .94. Flow experience is defined as the holistic experience that people feel when they act with total involvement, [43]. We built on the work of [59], [61] to determine respondents' flow experience as it related to their desire to retrieve FinTech resources from an online website program using self-directed learning. For this study, the measure included three items: Cronbach's alpha was .81. Computer self-efficacy is defined as an individual's perceptions about salient social referents that favor or oppose engaging in a particular behavior, [48]. For this study, computer self-efficacy was evaluated by questioning respondents about the extent to which they wanted to retrieve FinTech resources from an online website program using self-directed learning. For this study, the measure consisted of five items, and Cronbach's alpha was 0.94. Task-technology fit (TTF) measures one's belief that IT contributes to performance. Thus, users are more willing to accept this technology if it has a good fit with the tasks it supports. We adapted scales from [56], in which respondents were asked about the extent to which they wanted to retrieve FinTech resources from an online website program using self-directed learning. For this study, the measure included four items, and Cronbach's alpha was 0.88. According to [72], [73], an individual's perceived usefulness (PU) of behavior is equivalent to their overall assessment of the online website for self-directed learning. For this study, the measure consisted of four items, and Cronbach's alpha was 0.90.

Building on [7], [73], an individual's perceived ease-of-use (PEU) regarding behavior is equivalent to their overall assessment of the online website and the extent to which they want to retrieve FinTech resources from the site using self-directed learning. For this study, the measure included four items, and Cronbach's alpha was .84. Behavioral intentions based on [24] measure rated an individual's intentions by asking them about the extent to which they wanted to retrieve FinTech resources from an online website program using self-directed learning. For this study, the measure included three items, and Cronbach's alpha was .94.

4 Results and Analysis

This study used maximum likelihood estimation procedures to estimate, [74]. Following the guidelines proposed by [75], which suggest that the absolute value of skewness should be greater than three and the absolute value of kurtosis should be greater than 10, all the items in this research met the standard. Using (AMOS) 16.0 software, we analyzed (1) measurement assessment, (2) evaluation of the structural model fit, (3) hypothesis test of the research model, and (4) direct, indirect, and total effects.

4.1 Measurement Assessment

According to [76], items belonging to a specific construct should converge and share a high proportion of variance. Three major indicators of convergent validity are factor loading, average variance extracted (AVE), and construct reliability (CR), [77]. According to the statistics of confirmatory factor analysis (CFA), all of the construct factor loadings were greater than .70 for all items in all constructs. All of the construct values of AVE were also greater than .52, and all of the construct values of CR were greater than .80, as shown in Table 1 provided in the Appendix for clarity. Therefore, we can conclude that all constructs in the research model had acceptable convergence, [76], [77].

According to [77], discriminant validity is established when the square root of the average variance extracted (AVE) for each construct exceeds the correlations between that construct and all other constructs. As shown in Table 1 provided in the Appendix for clarity. The diagonal elements of the matrix represent the square roots of the AVE. In all cases, the diagonal values surpass the corresponding off-diagonal values, indicating that each construct shares more variance with its measurement items than with items associated with other constructs.

Discriminant validity was evaluated using two complementary approaches. First, based on the Fornell–Larcker criterion, the square root of each construct's AVE (diagonal elements) was greater than its correlations with other constructs (off-diagonal elements), suggesting that each construct shares more variance with its own indicators than with other constructs. Second, HTMT ratios were computed as an additional check; all HTMT values were below the conservative threshold of 0.85 (range = 0.42–0.78), further confirming that the constructs are empirically distinct.

4.2 Evaluation of the Structure Model Fit

CFA using AMOS 16.0 was conducted to validate the measurement model. The fit indices for the model were as follows: $\chi 2 = 974.23$; df = 367; norm $\chi 2 = 2.66$ (<3); goodness-of-fit index, GFI = .89 (>.80); adjusted GFI, AGFI = .87 (>.80); comparative fit index, CFI = .91 (>.90); and root mean square error approximation, RMSEA = .06 (<.08). Based on these values, most researchers would consider this model to be reasonable and representative of the data, [75], [76].

4.3 Hypothesis test of the Research Model

Figure 2 presents the properties of the causal paths (standardized path coefficients). The research model explains a substantial amount of the variance in task characteristics, flow experience, and computer self-efficacy toward TTF (R2 = .40), computer self-efficacy and TTF toward PEU (R2 = .44), TTF and PEU toward PU (R2 = .39), and PU and PEU toward behavioral intention (R2 = .48).

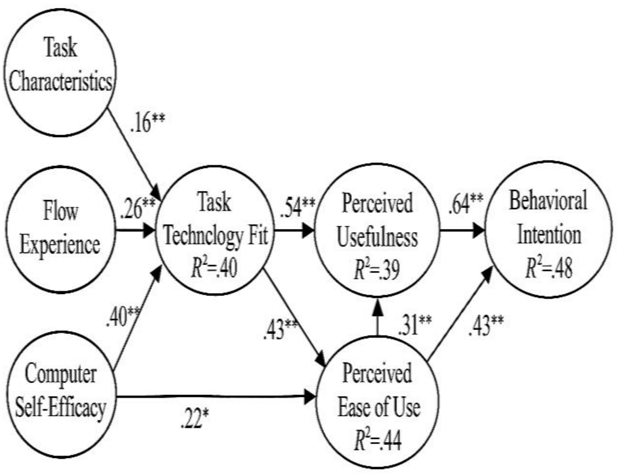

Fig. 2: The path coefficients of the research model
Source: created by the authors

Table 2 provided in the Appendix for clarity shows that the paths from task characteristics to TTF, flow experience to TTF, computer self-efficacy to TTF, computer self-efficacy to PEU, TTF to PU, PEU to PU, PU to behavioral intention, and PEU to behavioral intention are all significant, as indicated by a value of $p < .05$. These results indicate that all research hypotheses were supported.

4.4 Direct, Indirect, and Total Effects

[78] found that direct, indirect, and total effects are important in the interaction among latent variables for online learning environments. Using SEM, we obtained the direct, indirect, and total effects, as shown in Table 3, provided in the Appendix for clarity. The direct effect is associated with the following three antecedents: task characteristics (.16), flow experience (.26), and computer self-efficacy (.40). These three TTF components have been found to have a cooperative (i.e., positive) relationship with PEU/PU and behavioral intention in an online environment. The results also revealed that TTF had a more direct effect on PU (.54) than on PEU (.43). Furthermore, PU (.64) had a more substantial effect on behavioral intention than PEU (.43).

Figure 2 presents two mediation paths: (1) three antecedents via TTF (mediator) toward PU and (2) three antecedents via TTF (mediator) toward PEU. As shown in Table 3 provided in the Appendix for clarity, in the first path, we found that computer self-efficacy toward PU had the most significant indirect effect (.34); the second was flow experience (.14), followed by task characteristics (.11). In the second path, computer self-efficacy toward PEU had the most significant indirect effect (.17), followed by flow experience (.11), and task characteristics (.09).

The next set of paths included the following: (1) three antecedents via TTF concerning PU towards behavioral intention and (2) three antecedents via TTF concerning PEU towards behavioral intention. As shown in Table 3 provided in the Appendix for clarity, two paths revealed that computer self-efficacy, via the first path (TTF/PU), had the most significant indirect effect (.27), followed by flow experience (.16) and task characteristics (.14).

Finally, we identified the following two paths: (1) TTF via PU (mediator) toward behavioral intention and (2) TTF via PEU (mediator) toward behavioral intention. The former indirect effect was 0.35, the latter indirect effect was 0.27, and the total indirect effect was 0.62. The total effect is the sum of the direct and indirect effects. As shown in Table 3 provided in the Appendix for clarity, we identified six latent variables and 18 dependent latent variables. First, the total effect results revealed that four antecedents – task-technology fit (.16), PU (.11), PEU (.50), and behavioral intention (.14) of task characteristics have a cooperative relationship with task characteristics and TTF/PU/PEU/behavioral intention in online environments. Additionally, we found that about PU and PEU of the TAM model toward behavioral intention, PU (.64) had a slightly more substantial total effect than PEU (.63). Finally, for all latent variables (Table 3 provided in the Appendix for clarity), we found that TTF (.60), PU (.64), and PEU (.63) had an enhanced total effect toward behavioral intention.

5 Discussions and Conclusion

This research integrated the TAM and TTFM to determine the causal relationships in self-directed learning in online environments. We obtained the following research results using a structural equation model and empirical verification.

5.1 Major Finding

First, our research model has three antecedents for TTF: task characteristics, personal flow experience, and computer self-efficacy. In the present study, their direct effects were .16, .26, and .40, respectively. Computer self-efficacy had the most significant impact among them, indicating its role as a critical observation variable. These findings are consistent with research indicating a positive correlation between computer self-efficacy and virtual learning environments, [31]. Second, TTF (.43) and computer self-efficacy (.22) positively affected PEU, and the direct effect of TTF was better than that of computer self-efficacy. Third, TTF (.54) and PEU (.43) positively affected PU, and the direct effect of TTF exceeded that of PEU. Lastly, PU (.64) and PEU (.43) had a positive effect on behavioral intention, with PU having a more substantial effect.

The data analysis also indicated that PU and PEU mediated the relationship between TTF and behavioral intention through their effects on behavioral intention. Further, by comparing the mediating effects between TTF via PU to behavioral intention and TTF via PEU to behavioral intention, we found that the indirect impact of the former (.35) was more significant than the indirect effect of the latter (.27). Thus, TTF via PU toward behavioral intention had a more significant effect than that via PEU in online learning environments.

5.2 Implications

Previous studies using TAM solely explained approximately 40% of variance in behavioral intention toward online learning, [37]. The present research, which integrates the TAM and TTFM, demonstrated improved explanatory power. Furthermore, having better coordination among task characteristics, flow experience, and computer self-efficacy improves students' willingness to use online learning systems. Thus, cross-disciplinary knowledge is essential in motivating students to pursue self-learning activities in online environments [19], this knowledge should be integrated into the academic curriculum.

5.3 Conclusion

The present study offers worthwhile contributions to help clarify students' behavioral intentions in self-directed learning environments. Our findings indicate that TTF and computer self-efficacy have a positive effect on PEU and PU. Moreover, PU and PEU played a mediating role in the relationship between TTF and behavioral intention. Our results emphasize the need to guide students in such a way that they better understand the importance of cross-disciplinary knowledge attained through self-learning in online environments; introducing this to the academic curriculum as an important topic is expected to facilitate IT skill implementation by students.

5.4 Limitations and Future Research

First, this study sampled only college students in Taiwan. Future research should consider employing online community learning websites to conduct questionnaire distribution, thereby removing geographical restrictions and enhancing the external validity of the inferences. In addition, [79] found a significant difference between male and female students with regard to computer self-efficacy, PU, and PEU. Future research should explore further the key factors affecting behavioral intention in male and female groups using the TTFM. Moreover, this was a cross-sectional study; a longitudinal design would be more suitable for addressing the causal relationships between predictive variables and external criteria and should be considered for future implementation. Finally, this research focused on the establishment and demonstration of models. Future research should integrate the frequency of students' online learning activities and online time and incorporate this into the model to verify learning behavior intentions.

Acknowledgment:

This study was collaboratively undertaken by all three authors, who contributed to the research design, data analysis, and manuscript writing. The authors gratefully acknowledge the anonymous reviewers for their insightful comments and helpful suggestions, which substantially enhanced the quality of this work. The authors also wish to extend their appreciation to Dean Pi-Yueh Cheng for her continuous support, insightful guidance, and encouragement throughout the completion of this study.

References:

[1] Y. Huang, Self-directed learning and the effectiveness of e-learning in enterprises, International Journal of e-Education, e-Business, e-Management and e-Learning, Vol. 4, No. 4, 2014, pp. 313–317.

[2] L. Gerard, K. Wiley, A. DeBarger, S. Bichler, A. Bradford, and M. Linn, Self-directed science learning during COVID-19 and beyond, Journal of Science Education and Technology, Vol. 31, 2022. https://doi.org/10.1007/s10956-021-09953-w.

[3] F. Karakas and A. Manisaligil, Reorienting self-directed learning for the creative digital era, European Journal of Training and Development, Vol. 36, 2012, pp. 712–731. https://doi.org/10.1108/03090591211255557.

[4] R. G. Brockett and R. Hiemstra, Self-direction in adult learning: Perspectives on theory, research, and practice, Routledge, 1991. https://doi.org/10.4324/9780429457319.

[5] G. L. Confessore and S. J. Confessore, Guideposts to self-directed learning, Organization Design and Development Inc., 1992.

[6] M. J. Culnan, The dimensions of perceived accessibility to information: Implications for the delivery of information systems and services, Journal of the American Society for Information Science, Vol. 36, 1985, pp. 302–308. https://doi.org/10.1002/asi.4630360504.

[7] F. D. Davis, Perceived usefulness, perceived ease of use, and user acceptance of information technology, MIS Quarterly, Vol. 13, No. 3, 1989, pp. 319–340. https://doi.org/10.2307/249008.

[8] C. W. Choo, Environmental scanning by CEOs in two Canadian industries, Journal of the American Society for Information Science and Technology, Vol. 44, No. 4, 1993, pp. 194–204.

[9] M. L. Fleming and W. H. Levie, Instructional message design: Principles from the behavioral and cognitive science, 2nd ed., Prentice Hall, 1993. ISBN: 0-87778-104-4.

[10] J. E. Klobas and L. A. Clyde, Adults learning to use the Internet, Library & Information Science Research, Vol. 22, No. 1, 2000, pp. 5–34. DOI: Retrieved April 26, 2026.

[11] J. D'Ambra and C. Wilson, Explaining perceived performance of the World Wide Web: Uncertainty and the task–technology fit model, Internet Research, Vol. 14, No. 4, 2004, pp. 294–310. https://doi.org/10.1108/10662240410555315.

[12] H.-H. Chang, Intelligent agent's technology characteristics applied to online auctions' task: A combined model of TTF and TAM, Technovation, Vol. 28, No. 9, 2008, pp. 564–577. https://doi.org/10.1016/j.technovation.2008.03.006.

[13] G. Chang and L. Caneday, Web-based GIS in tourism information search: An analysis of the effect of socioeconomic characteristics on perception and behavior, Loisir et Société / Society and Leisure, Vol. 35, No. 1, 2012, pp. 155–174.

[14] M. T. Dishaw and D. M. Strong, Extending the technology acceptance model with task–technology fit constructs, Information & Management, Vol. 36, No. 1, 1999, pp. 9–21. https://doi.org/10.1016/S0378-7206(98)00101-3.

[15] D. L. Goodhue and R. L. Thompson, Task–technology fit and individual performance, MIS Quarterly, Vol. 19, No. 2, 1995, pp. 213–236. https://doi.org/10.2307/249689.

[16] B. Taylor, Self-directed learning: Revisiting an idea most appropriate for middle school students, ERIC Document ED395287, 1995, [Online]. https://files.eric.ed.gov/fulltext/ED395287.pdf (Accessed Date: February 3, 2026).

[17] R. J. Murnane and F. Levy, Teaching the New Basic Skills: Principles for Educating Children to Thrive in a Changing Economy, New York: Free Press, 1996.

[18] H. Segars and V. Grover, Re-examining perceived ease of use and usefulness: A confirmatory factor analysis, MIS Quarterly, Vol. 17, No. 4, 1993, pp. 517–525. https://doi.org/10.2307/249590.

[19] P. A. Pavlou and M. Fygenson, Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior, MIS Quarterly, Vol. 30, No. 1, 2006, pp. 115–143. https://doi.org/10.2307/25148720.

[20] H. B. Long, College students' self-directed learning readiness and educational achievement, in Self-Directed Learning: Consensus and Conflict, H. B. Long and Associates, Eds., 1990, pp. 107–122.

[21] M. G. Morris and A. Dillon, How user perceptions influence software use, IEEE Software, Vol. 14, No. 4, 1997, pp. 58–65. https://doi.org/10.1109/52.595956.

[22] M. Fishbein and I. Ajzen, Belief, attitude, intention and behavior: An introduction to theory and research, Addison-Wesley, 1975.

[23] I. Ajzen and T. J. Madden, Prediction of goal-directed behavior: Attitude, intentions, and perceived behavioral control, Journal of Experimental Social Psychology, Vol. 22, No. 5, 1986, pp. 453–474. https://doi.org/10.1016/0022-1031(86)90045-4.

[24] I. Ajzen, The theory of planned behavior, Organizational Behavior and Human Decision Processes, Vol. 50, No. 2, 1991, pp. 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

[25] B. J. Lin and W. B. Chiou, Undergraduates' intentions to take a second language proficiency test, Psychological Reports, Vol. 106, No. 3, 2010, pp. 798–810. https://doi.org/10.2466/pr0.106.3.798-81.

[26] V. Venkatesh, C. Speier, and M. G. Morris, User acceptance enablers in individual decision making about technology, Decision Sciences, Vol. 33, No. 2, 2002, pp. 297–315. https://doi.org/10.1111/j.1540-5915.2002.tb01646.x.

[27] T. S. H. Teo, V. K. G. Lim, and R. Y. C. Lai, Intrinsic and extrinsic motivation in Internet usage, Omega, Vol. 27, No. 1, 1999, pp. 25–37. https://doi.org/10.1016/S0305-0483(98)00028-0.

[28] D. A. Adams, R. R. Nelson, and P. A. Todd, Perceived usefulness, ease of use, and usage of information technology: A replication, MIS Quarterly, Vol. 16, No. 2, 1992, pp. 227–247. https://doi.org/10.2307/249577.

[29] R. Hendrickson, P. D. Massey, and T. P. Cronan, On the test–retest reliability of perceived usefulness and perceived ease of use scales, MIS Quarterly, Vol. 17, No. 2, 1993, pp. 227–230. https://doi.org/10.2307/249803.

[30] D. H. Schunk, Self-regulation of self-efficacy and attributions in academic settings, in Self-regulation of learning and performance, 1994, pp. 75–99.

[31] M. J. Simmering, C. Posey, and G. Piccoli,

Computer self-efficacy and motivation to learn in a self-directed online course, Decision Sciences Journal of Innovative Education, Vol. 7, No. 1, 2009, pp. 99–121. https://doi.org/10.1111/j.1540-4609.2008.00207.x.

[32] L. K. Trevino and J. Webster, Flow in computer-mediated communication, Communication Research, Vol. 19, No. 5, 1992, pp. 539–573. https://doi.org/10.1177/009365092019005001

[33] G. M. Marakas, M. Y. Yi, and R. D. Johnson, The multilevel and multifaceted character of computer self-efficacy, Information Systems Research, Vol. 9, No. 2, 1998, pp. 126–163. https://doi.org/10.1287/isre.9.2.126.

[34] Q. Hu and T. Dinev, Is spyware an Internet nuisance or public menace?, Communications of the ACM, Vol. 48, No. 8, 2005, pp. 61–66.

[35] M. Hsu and C. Chiu, Internet self-efficacy and electronic service acceptance, Decision Support Systems, Vol. 38, 2004, pp. 369–381. https://doi.org/10.1016/j.dss.2003.08.001.

[36] F. Pajares, Self-efficacy beliefs, motivation, and achievement in writing, Reading & Writing Quarterly, Vol. 19, No. 2, 2003, pp. 139–158.

[37] P. Legris, J. Ingham, and P. Collerette, Why do people use information technology? A critical review of the technology acceptance model, Information & Management, Vol. 40, No. 3, 2003, pp. 191–204. https://doi.org/10.1016/S0378-7206(01)00143-4.

[38] M.-H. Hsiao, A conceptual framework for technology-enabled and technology-dependent user behavior toward device mesh and mesh app, Future Business Journal, Vol. 4, No. 1, 2018, pp. 130–138. https://doi.org/10.1016/j.fbj.2018.03.003.

[39] A. Isaac, A. Aldholay, Z. Abdullah, and T. Ramayah, Online learning usage within Yemeni higher education, Computers & Education, Vol. 136, 2019, pp. 113–129. https://doi.org/10.1016/j.compedu.2019.02.012.

[40] M. Junglas, C. Abraham, and R. T. Watson, Task–technology fit for mobile locatable information systems, Decision Support Systems, Vol. 45, No. 4, 2008, pp. 1046–1057. https://doi.org/10.1016/j.dss.2008.02.007.

[41] H.-C. Lee, H. K. Cheng, and H.-H. Cheng, An empirical study of mobile commerce in the insurance industry, Decision Support Systems, Vol. 43, No. 1, 2007, pp. 95–110. 10.1016/j.dss.2005.05.008.

[42] J. Webster, L. K. Trevino, and L. Ryan, The dimensionality and correlates of flow in human–computer interactions, Computers in Human Behavior, Vol. 9, No. 4, 1993, pp. 411–426. https://doi.org/10.1016/0747-5632(93)90032-N.

[43] M. Csikszentmihalyi, Beyond boredom and anxiety, Jossey-Bass, 2000, [Online]. https://psycnet.apa.org/record/2000-12701-000 (Accessed Date: February 3, 2026).

[44] M. Csikszentmihalyi and J. LeFevre, Optimal experience in work and leisure, Journal of Personality and Social Psychology, Vol. 56, No. 5, 1989, pp. 815–822. https://doi.org/10.1037/0022-3514.56.5.815.

[45] S. Y. Tzeng, K. Y. Lin, and C. Y. Lee, Predicting college students' adoption of technology for self-directed learning, Frontiers in Psychology, Vol. 13, 2022. https://doi.org/10.3389/fpsyg.2022.865803.

[46] A. Bandura, Self-efficacy: Toward a unifying theory of behavioral change, Psychological Review, Vol. 84, No. 2, 1977, pp. 191–215. https://doi.org/10.1037/0033-295X.84.2.191.

[47] A. Bandura, Social foundations of thought and action: A social cognitive theory, Prentice-Hall, 1986, [Online]. https://www.semanticscholar.org/paper/78c6775fccdbbed66f823dae2cfa01570ecb3c05 (Accessed Date: February 3, 2026).

[48] D. R. Compeau and C. A. Higgins, Computer self-efficacy: Development of a measure and initial test, MIS Quarterly, Vol. 19, No. 2, 1995, pp. 189–211. https://doi.org/10.2307/249688.

[49] M. Bong and E. M. Skaalvik, Academic self-concept and self-efficacy: How different are they really?, Educational Psychology Review, Vol. 15, No. 1, 2003, pp. 1–40. https://doi.org/10.1023/A:1021302408382.

[50] E. A. Linnenbrink and P. R. Pintrich, The role of self-efficacy beliefs in student engagement and learning in the classroom, Reading & Writing Quarterly, Vol. 19, No. 2, 2003, pp. 119–137. https://doi.org/10.1080/10573560308223.

[51] C.-S. Ong, J.-Y. Lai, and Y.-S. Wang, Factors affecting engineers' acceptance of asynchronous e-learning systems in high-tech companies, Information & Management, Vol. 41, No. 6, 2004, pp. 795–804. https://doi.org/10.1016/j.im.2003.08.012.

[52] B. Arbaugh, Virtual classroom characteristics

and student satisfaction with Internet-based MBA courses, Journal of Management Education, Vol. 24, No. 1, 2000, pp. 32–54. https://doi.org/10.1177/105256290002400104

[53] J. Burns, J. Clift, and J. Duncan, Understanding of understanding: Implications for learning and teaching, British Journal of Educational Psychology, Vol. 61, No. 3, 1991, pp. 276–289, [Online]. https://bpspsychub.onlinelibrary.wiley.com/doi/abs/10.1111/j.2044-8279.1991.tb00985.x (Accessed Date: February 3, 2026).

[54] G. H. Subramanian, A replication of perceived usefulness and perceived ease of use measurement, Decision Sciences, Vol. 25, Nos. 5–6, 1994, pp. 863–873. https://doi.org/10.1111/j.1540-5915.1994.tb01873.x.

[55] S. Attaran and M. Attaran, Collaborative computing technology: The hot new managing tool, Journal of Management Development, Vol. 21, No. 8, 2002, pp. 598–609. https://doi.org/10.1108/02621710210437572.

[56] N. Avouris, A. Dimitracopoulou, and V. Komis, On analysis of collaborative problem solving, Computers in Human Behavior, Vol. 19, No. 2, 2003, pp. 147–167. https://doi.org/10.1016/S0747-5632(02)00056-0.

[57] T. P. Novak, D. L. Hoffman, and Y.-F. Yung, Measuring the customer experience in online environments, Marketing Science, Vol. 19, No. 1, 2000, pp. 22–42. https://doi.org/10.1287/mksc.19.1.22.15184.

[58] J. A. Ghani and S. P. Deshpande, Task characteristics and the experience of optimal flow, The Journal of Psychology, Vol. 128, No. 4, 1994, pp. 381–391. https://doi.org/10.1080/00223980.1994.9712742.

[59] A. Theodorou, L. Hatzithomas, T. Fotiadis, A. Diamantidis, and A. Gasteratos, The impact of the COVID-19 pandemic on online consumer behavior, Sustainability, Vol. 15, No. 3, 2545, 2023. https://doi.org/10.3390/su15032545.

[60] Y. Wang, A comparative study of Chinese and American preservice teachers' intention to teach online, Education and Information Technologies, 2022. 10.1007/s10639-022-11442-5.

[61] G. R. Norman and H. G. Schmidt, The psychological basis of problem-based learning: A review of the evidence, Academic Medicine, Vol. 67, No. 9, 1992, pp. 557–565. doi: 10.1097/00001888-199209000-00002.

[62] R. Bary and M. Rees, Is self-directed learning the key skill for tomorrow's engineers?, European Journal of Engineering Education, Vol. 31, No. 1, 2006, pp. 73–81. https://doi.org/10.1080/03043790500429021.

[63] K. Mathieson, E. Peacock, and W. W. Chin, Extending the technology acceptance model: The influence of perceived user resources, ACM SIGMIS Database, Vol. 32, No. 3, 2001, pp. 86–112. https://doi.org/10.1145/506724.506730..

[64] C.-S. Ong and J.-Y. Lai, Gender differences in perceptions and relationships among dominants of e-learning acceptance, Computers in Human Behavior, Vol. 22, No. 5, 2006, pp. 816–829. https://doi.org/10.1016/j.chb.2004.03.006.

[65] V. Z. Vanduhe, M. Nat, and H. F. Hasan, Continuance intentions to use gamification for training in higher education, IEEE Access, Vol. 8, 2020, pp. 21473–21484. https://doi.org/10.1109/ACCESS.2020.2966179.

[66] M. Chen, M. L. Gillenson, and D. L. Sherrell, Enticing online consumers: An extended technology acceptance perspective, Information & Management, Vol. 39, No. 8, 2002, pp. 705–719. https://doi.org/10.1016/S0378-7206(01)00127-6.

[67] H. Lou, W. Luo, and D. M. Strong, Perceived critical mass effect on groupware acceptance, European Journal of Information Systems, Vol. 9, No. 2, 2000, pp. 91–103. https://doi.org/10.1057/palgrave.ejis.3000358.

[68] K. Mathieson, Predicting user intentions: Comparing the technology acceptance model with the theory of planned behavior, Information Systems Research, Vol. 2, No. 3, 1991, pp. 173–191. https://doi.org/10.1287/isre.2.3.173.

[69] K. Mathieson and M. Keil, Beyond the interface: Ease of use and task/technology fit, Information & Management, Vol. 34, No. 4, 1998, pp. 221–230. https://doi.org/10.1016/S0378-7206(98)00058-5.

[70] S. Taylor and P. A. Todd, Understanding information technology usage: A test of competing models, Information Systems Research, Vol. 6, No. 2, 1995, pp. 144–176.

[71] R. W. Brislin, Comparative research methodology: Cross-cultural studies, International Journal of Psychology, Vol. 11,

No. 3, 1976, pp. 215–229. https://doi.org/10.1080/00207597608247359.

[72] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, User acceptance of computer technology: A comparison of two theoretical models, Management Science, Vol. 35, No. 8, 1989, pp. 982–1003. https://doi.org/10.1287/mnsc.35.8.982.

[73] J.-W. Moon and Y.-G. Kim, Extending the TAM for a World Wide Web context, Information & Management, Vol. 38, No. 4, 2001, pp. 217–230. https://doi.org/10.1016/S0378-7206(00)00061-6.

[74] P. J. Curran, S. G. West, and J. F. Finch, The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis, Psychological Methods, Vol. 1, No. 1, 1996, pp. 16–29. https://doi.org/10.1037/1082-989X.1.1.16.

[75] R. B. Kline, Principles and practices of structural equation modeling, 2nd ed., Guilford Press, 2005, [Online]. https://psycnet.apa.org/record/2005-03476-000 (Accessed Date: February 3, 2026).

[76] J. F. Hair Jr., R. E. Anderson, R. L. Tatham, and W. C. Black, Multivariate data analysis, 7th ed., Prentice Hall, 2009. ISBN: 9781292021904.

[77] C. Fornell and D. F. Larcker, Evaluating structural equation models with unobservable variables and measurement error, Journal of Marketing Research, Vol. 18, No. 1, 1981, pp. 39–50. https://doi.org/10.2307/3151312.

[78] K. A. Bollen, Structural equations with latent variables, John Wiley & Sons, 1989. https://doi.org/10.1002/9781118619179.

[79] L. Olfman and M. Mandviwalla, Conceptual versus procedural software training for graphical user interfaces, MIS Quarterly, Vol. 18, No. 4, 1994, pp. 405–426. https://doi.org/10.2307/24952.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

All authors equally contributed to the present research at all stages, including the formulation of the research problem, research design, data collection and analysis, interpretation of results, and manuscript preparation.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

The authors gratefully acknowledge the anonymous reviewers for their constructive comments and insightful suggestions, which have significantly enhanced the quality of this manuscript. The authors are also deeply indebted to Dean Pi-Yueh Cheng for her valuable guidance and continuous support. Any remaining errors are the responsibility of the authors.

Conflict of Interest

The authors have no conflicts of interest to declare relevant to the content of this article.

APPENDIX

Table 1. Descriptive statistics of all constructs as well as their inter-correlations

	VAR	1	2	3	4	5	6	7
1	TC	(.85)	.52**	.23**	.33**	.29**	.42**	.38**
2	FE		(.76)	.25**	.35**	.31**	.52**	.40**
3	CSE			(.97)	.49**	.36**	.24**	.27**
4	TTF				(.80)	.49**	.38**	.36**
5	PU					(.92)	.31**	.40**
6	PEOU						(.85)	.44**
7	BI							(.80)
	Mean	5.92	5.23	5.08	5.41	5.56	5.08	5.54
	SD	0.97	1.06	1.11	1.04	1.06	1.09	1.07
	CR	.94	.81	.94	.88	.95	.91	.84
	AVE	.73	.58	.76	.64	.84	.72	.64
	OR	1-7	1-7	1-7	1-7	1-7	1-7	1-7

Var=Variable, TC=Task characteristics, FE=Flow experience, CSE=Computer self-efficacy, TTF= Task-technology fit, PU=Perceived usefulness, PEOU=Perceived ease-of-use, BI=Behavioral intention, S.D.=Standard deviation, CR=Composite reliability, AVE= Average variance extracted, OR=Observed range. Diagonal: square root of AVE from observed variables; off-diagonal: correlations between constructs * =p < .05; **= p < .01; ***= p < .001

Source: created by the authors

Table 2. Hypotheses-testing

The relationship of the **path**		**Path coefficient**	**Hypotheses**
Task characteristics	TTF	.16**	Hypothesis 1 received empirical support.
Flow experience	TTF	.26**	Hypothesis 2 received empirical support.
Computer self-efficacy	TTF	.40*	Hypothesis 3 received empirical support.
Computer self-efficacy	PEOU	.22*	Hypothesis 4 received empirical support.
Task-technology fit	PEOU	.43*	Hypothesis 5 received empirical support.
Task-technology fit	PU	.54*	Hypothesis 6 received empirical support.
Perceived ease-of-use	PU	.31*	Hypothesis 7 received empirical support.
Perceived usefulness	BI	.64**	Hypothesis 8 received empirical support.
Perceived ease-of-use	BI	.43**	Hypothesis 9 received empirical support.

*=p < .05; **= p < .01; ***= p < .001

Source: created by the authors

Table 3. The direct, indirect, and total effect

Latent variable	**Dependent latent variable**	**Direct effect**	**Indirect effect**	**Total effect**

Task characteristics	TTF	0.16	N.A.	0.16
	PU	N.A.	0.11	0.11
	PEOU	0.43	0.07	0.50
	BI	N.A.	0.14	0.14
Flow experience	TTF	0.26	N.A.	0.26
	PU	N.A.	0.18	0.18
	PEOU	N.A.	0.11	0.11
	BI	N.A.	0.16	0.16
Computer self-efficacy	TTF	0.40	N.A.	0.40
	PU	N.A.	0.34	0.34
	PEOU	0.22	0.17	0.39
	BI	N.A.	0.27	0.27
Task-technology fit	PU	0.54	0.13	0.67
	PEOU	0.43	N.A.	0.43
	BI	N.A.	0.62	0.62
Perceived ease-of-use	PU	0.31	N.A.	0.31
	BI	0.43	.020	0.63
Perceived usefulness	BI	0.64	N.A.	0.64

Source: created by the authors