Innovation &
Management
Review

85

Received 5 November 2024
Revised 29 July 2025
15 February 2026
29 April 2026
Accepted 11 May 2026

Evolving ease: the dynamic moderating role of perceived ease of use in the technology acceptance model

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Abstract

Purpose – This study aims to address ambiguities in the technology acceptance model (TAM) by examining the conditions under which TAM constructs positively affect technology adoption, focusing on the interactive effects of perceived ease of use (PEOU), perceived usefulness (PU) and subjective norms (SN) on behavioral intention (BI).

Design/methodology/approach – The research investigates multiple technologies over an extended period, examining conditions at the adoption moment and after three months of usage. A mediated-moderation analysis was employed to explore the interactions among TAM constructs.

Findings – PEOU functions as a moderator in the relationship among PU, SN and BI. The effects of PU and SN on BI are heightened when the technology is perceived as easy to use. After three months, a higher level of PEOU is required to sustain continued use.

Practical implications – The findings underscore the importance of prioritizing ease of use in technology development and marketing, as it significantly influences the impact of recommendations and PU on adoption decisions.

Originality/value – This study introduces a novel approach by examining PEOU as a moderator within the TAM framework, providing new insights into the interactive effects of TAM constructs on technology adoption. The research contributes to resolving conflicting findings in previous TAM studies and offers valuable guidance for sustaining new technology adoption.

Keywords Technology acceptance model, Technology adoption, Continued use intention, Perceived ease of use, UTAUT

Paper type Research article

Introduction

The concept of technology adoption has long been a pivotal point for researchers seeking to understand how individuals embrace new technologies. Extensive research has explored technology adoption, primarily using the technology acceptance model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT), later developed by Venkatesh, Morris, Davis, and Davis (2003). Since its introduction, researchers have aimed to enhance TAM's explanatory power through various methods, such as identifying additional

Funding: This research was supported by the Bar-Ilan University Research Scholarship Grants in 2022.
Disclosure statement: No potential conflict of interest was reported by the author(s).

Innovation & Management Review
Vol. 23, 2026
pp. 85-98
Emerald Publishing Limited
2515-8961
DOI 10.1108/INMR-08-2024-0203

constructs – thus expanding the model (Abdullah & Ward, 2016; Razmak & Bélanger, 2018; Acikgoz & Vega, 2022; Faqih, 2022) – and identifying factors that moderate TAM constructs (Schepers & Wetzels, 2007; Abegao Neto & Figueiredo, 2023). TAM focuses on variables like perceived ease of use (PEOU) and perceived usefulness (PU) and their impact on technology adoption. However, many previous studies have focused on individual technologies, examining them at a single point in time upon adoption. Limited research has explored changes in consumer attitude over time following the adoption of these technologies; studies (Birnholtz, 2010; Šumak, Pušnik, Heričko, & Šorgo, 2017) have shown that, in many cases, users abandon technologies they initially adopted. This is why we propose that a longitudinal approach would provide a more comprehensive understanding of technology adoption.

Furthermore, findings from previous studies on technology adoption have been inconclusive regarding the roles of PEOU and PU in shaping user intentions and behaviors (Kucukusta, Law, Besbes, & Legohérel, 2015; Abdullah & Ward, 2016; Wu & Chen, 2017; Adnan, Irvine, Williams, Harris, & Antonacci, 2025). Similarly, TAM2 (Venkatesh & Davis, 2000), an extension of TAM that also incorporates subjective norms (SN), suggests that individuals may adopt technology not solely based on their own convictions, but also on opinions of others. However, TAM2 has also produced mixed results concerning the influence of SN on behavioral intention (BI) (Cheung & Vogel, 2013; Suki & Suki, 2017; Ursavaş, Yalçın, İslamoğlu, Bakır-Yalçın, & Cukurova, 2025). Considering the inconsistency in the effects of SN, PEOU and PU on intention to adopt new technologies, our research aims to elucidate these mixed findings and propose an innovative approach to addressing the question of under what conditions these factors positively influence technology adoption. Rather than viewing these inconsistencies as contradictory, we argue that they point to the importance of identifying the conditions and mechanisms under which core TAM relationships are more or less likely to hold.

Additionally, our research expands the scope of current studies by investigating multiple technologies over an extended period – we explored these conditions during the adoption per se and after three months of usage.

Over the years, many studies have discussed several types of moderators for TAM, some related to personal traits such as age and gender (Venkatesh & Davis, 2000), technology type or culture (Schepers & Wetzels, 2007), risk perception (Tsai, 2024) and more.

Most of these moderators are treated as external factors that shape technology adoption. However, it is also possible that one of TAM's core constructs influences when and how the relationships within the model operate. Building on this idea, and in light of the mixed findings regarding the effects of PEOU and PU on BI, we suggest that PEOU, one of the model constructs, actually acts as a moderator in the relationship between PU, SN and BI. Therefore, PU and SN become more predictive when the technology is perceived as easy to use. This study contributes in a three-fold manner.

Firstly, by shedding light on the circumstances in which each TAM variable impacts BI.

Secondly, it addresses the limitations in previous studies that often focus on specific technology adoption contexts by examining various changes across different technologies. It is important to note that here the term "different technologies" does not refer to the simultaneous adoption of several technologies by the same user; instead, the emphasis lies in not concentrating on the adoption of a particular technology, like most studies within this field (Amboage, Monteiro, & Bortoluzzo, 2024; Acikgoz & Vega, 2022). Rather, our focus is on various technologies that were adopted in response to COVID-related restrictions.

Thirdly, given the limited number of longitudinal studies in TAM literature and the fact that existing ones, such as Tao, Wang, Wang, Zhang and Zhang (2022), focus on a particular context within the COVID-19 pandemic, this study offers a unique contribution by examining two distinct phases of technology adoption: an initial phase under full lockdown, when usage was mandatory, and a later phase after restrictions were lifted, when continued use became voluntary. Importantly, the longitudinal design in this study captures not only changes associated with increased familiarity over time but also a fundamental shift in contextual conditions: from enforced to voluntary technology use. This design has enabled us to assess how BI evolves under shifting external conditions. Our research findings offer valuable insights by highlighting the significance of PEOU not only in the adoption stage but also, and even more prominently, throughout the continuous usage stage. This understanding might contribute to achieving higher user retention rates.

Theory development

Technology acceptance model

Since its introduction, the TAM has been increasingly applied across a wide range of domains, reflecting its growing relevance in understanding technology adoption (Marikyan, Papagiannidis, & Stewart, 2023). Its extensions like TAM2 (Venkatesh & Davis, 2000), UTAUT (Venkatesh *et al.*, 2003) and UTAUT2 (Venkatesh, Thong, & Xu, 2012) were developed to account for additional variables and contexts, offering a deeper and more detailed understanding of how people interact with technology. TAM, initially introduced by Davis (1989), outlines PU and PEOU as fundamental and distinct constructs that are central in influencing decisions regarding the adoption of information technology. Over the years, scholars have applied it to a wide range of contexts, including flight ticket booking (Suki & Suki, 2017); telehealth technology (Wade, Cartwright, & Shaw, 2012; Tsai, Cheng, Tsai, Hung, & Chen, 2019); fitness apps (Cho, Chi, & Chiu, 2020); voice assistants (Acikgoz & Vega, 2022); mobile payments (Abegao Neto & Figueiredo, 2023); Near Field Communication mobile wallets (Shin & Lee, 2021); the Internet of Things (IoT) (Tsai, 2024); artificial intelligence (AI) technologies (Shao, Nah, Makady, & McNealy, 2025) and more. A recent meta-analysis on technology acceptance (Marikyan *et al.*, 2023), which reviewed data from 693 papers, found that TAM and UTAUT are the most reliable and effective theories for examining factors related to the three main outcomes: attitude, intention to use technology and actual usage behavior.

Perceived usefulness

PU, defined by Davis (1989) as the extent to which an individual believes that using a particular system would enhance their job performance, is a critical construct in both the TAM and the UTAUT. This construct is hypothesized to play a pivotal role in shaping BI to adopt new technologies (Davis, 1989; Venkatesh *et al.*, 2003). A growing body of research continues to highlight the strong and consistent link between PU and BI to adopt technology. While PU was originally studied in work-related systems, its relevance now spans a wide range of personal and everyday digital interactions. Recent studies have shown its impact on areas such as AI-powered learning platforms (Kim, Kim, & Shin, 2009) and mobile health applications (Tao *et al.*, 2020a, b; Luo *et al.*, 2024), in which users' perceptions of usefulness were key drivers of adoption decisions. Moreover, several scholars suggest that PU is a stronger driver of BI than other factors. For example, Nagy and Hajdú (2021), in their study of AI-powered web shopping in Hungary, found that PU was more important than PEOU in shaping users' attitude and purchase intention. Similarly, Tao *et al.* (2020a, b) reported a stronger link between PU and adoption intention for consumer health information technologies than that between PEOU and adoption intention.

Perceived ease of use

PEOU is a key element in the TAM, originally defined by Davis (1989) as "the degree to which a person believes that using a particular system would be free of effort." According to Davis, when users perceive a system as easy to use, they are more likely to accept and adopt it. This idea was later adapted in the UTAUT, when Venkatesh *et al.* (2003) referred to it as "effort expectancy," reflecting the same core notion. Recent studies continue to explore the role of PEOU in various technological contexts. For example, Abegao Neto & Figueiredo (2023), examining mobile payment use in Brazil, found that simpler interfaces significantly increased users' willingness to adopt the technology.

That said, the effect of PEOU on BI remains debatable. While many studies have found a positive link between PEOU and technology adoption (Hu, Clark, & Ma, 2003; Liu, Li, & Carlsson, 2010; Zhao, Ni, & Zhou, 2018; Adnan *et al.*, 2025), others suggest the relationship may be more complex. Two recent meta-analyses (Zhao *et al.*, 2018; Adnan *et al.*, 2025) confirmed that PEOU plays a significant role in shaping user intention to adopt mobile health technologies. Conversely, other studies have found no significant effect of PEOU on technology adoption (Liu *et al.*, 2010; Legramante, Azevedo, & Azevedo, 2023; Yuliadewi, Kusuma, & Atmaja, 2024). Specifically, Yuliadewi *et al.* (2024), examining post-pandemic use of online technology, found that PEOU did not have a significant direct effect on BI. Instead, its influence was indirect, operating through users' attitude toward the technology. Similarly, Legramante *et al.* (2023), in their study of Moodle's continuity of use, reported that PEOU did not significantly affect either user satisfaction or BI. These mixed findings highlight the complex nature of this relationship and underscore the need for further investigation.

Subjective norms

SN, as defined by Venkatesh and Davis (2000), refers to the perceived social pressure for the adoption of a specific behavior. This construct, initially introduced in TAM2, encapsulates the social influence exerted by family, friends and prominent individuals. Fishbein and Ajzen (1975) defined SN as perceived pressures on a person to perform a given behavior and the person's motivation to comply with those pressures. The UTAUT also addresses SN as "social influence," which measures the degree to which an individual perceives that important others believe they should use the new system (Venkatesh *et al.*, 2003). Subsequently, a considerable body of research explored the influence of SN on technology adoption (Schepers and Wetzels, 2007; Kim *et al.*, 2009; Baker, Al-Gahtani, and Hubona, 2010; Cheung & Vogel, 2013; Suki and Suki, 2017; Ibrahim, Münscher, Daseking and Telle, 2025, to name a few). Some studies considered SN as a direct determinant of technology adoption (Kim *et al.*, 2009; Cheung & Vogel, 2013), while others proposed a pathway in which SN affects PU and/or PEOU, impacting technology adoption (Abdullah, Ward, & Ahmed, 2016; Jin, 2014).

Nonetheless, these investigations yielded inconsistent findings regarding the effect of SN on the intention to adopt technology. While certain studies have found a positive influence (Baker *et al.*, 2010; Zhang & Xu, 2024), others reported no significant impact on BI from using new technology (Suki & Suki, 2017; Wu & Chen, 2017; Ursavaş *et al.*, 2025). For example, Zhang and Xu (2024) found that subjective norms positively influenced perceived usefulness in an extended TAM framework, thereby contributing to scholars' intentions to adopt Open Communication Science practices. In contrast, Ursavaş *et al.* (2025) investigated the factors influencing higher education students' intention to use generative AI tools and found that SN had only a limited influence. These findings challenge traditional assumptions within the TAM regarding the role of social pressure in technology adoption. The results suggest that, in the context of GenAI, students may rely more on their personal perceptions and evaluations of the technology than on the opinions or expectations of others.

Taken together, the mixed findings regarding the effect of SN on BI suggest that social influence does not operate in a uniform way across all technology adoption contexts. These inconsistencies point to the possibility that SN impact depends on specific conditions and mechanisms. Prior studies indicate that social influence may shape adoption decisions indirectly (Abdullah *et al.*, 2016; Jin, 2014). This perspective suggests that the key question is not whether SN matters, but how and through which pathways they influence BI. Building on this reasoning, the present study examines both (1) the direct effect of SN and (2) their indirect effect through PU, leading to the following hypotheses:

H1. Subjective norms will have a positive direct effect on behavioral intention.

H2. Subjective norms will have a positive direct effect on the perceived usefulness of a technology.

H3. Perceived usefulness will mediate the effect of subjective norms on behavioral intention.

Some scholars (Subramanian, 1994; Teo, Lim, & Lai, 1999; Sun & Zhang, 2006) attributed the insignificant effects of PEOU on BI to the nature of the systems covered by their studies. They argued that complexity may moderate the effect of PEOU on BI to adopt a new technology. Moreover, Brokman-Meltzer, Perez, & Gelbard (2021), in the context of project management research, found that the level of objective complexity was similar to project managers' perception of complexity (perceived complexity). We integrate this claim with the notion that PEOU was introduced to the TAM due to earlier research emphasizing the role of complexity in innovation adoption theory. Rogers and Shoemaker (1971) defined the perceived complexity of a technology as "the degree to which an innovation is perceived as relatively difficult to understand or use". Due to the parallel meaning of PEOU and perceived complexity, we expect PEOU to play a moderating role in the effect of TAM constructs on BI, potentially explaining the mixed findings concerning the impact of this construct on PU and BI. Therefore, we argue that H1–H3 hold only when PEOU is high. In contrast, when PEOU is low, we expect these effects to be diminished.

This reasoning allows us to move from prior explanations of complexity-related effects to a conditional view of PEOU as a boundary condition within the TAM framework, leading to the following hypotheses.

H4. Perceived ease of use will moderate the effect of perceived usefulness on behavioral intention.

H5. Perceived ease of use will moderate the mediation of perceived usefulness in the effect of subjective norms on behavioral intention.

Inspired by Venkatesh and Davis (2000), we also investigated whether perceptions of SN, PU and PEOU, as collected at time 1, can predict BI over time. Longitudinal research in the context of technology adoption was originally motivated by the assumption that user experience and familiarity with a given technology evolve over time, thereby shaping user perception and intention to adopt it (Venkatesh & Davis, 2000). In the present study, however, the passage of time reflects not only increased experience with the adopted technology but also a meaningful shift in contextual conditions. Specifically, technology use was initially imposed during COVID-19 lockdowns and later became voluntary, as restrictions were lifted. This unique context allows us to examine whether the relationships proposed by TAM persist not only as a function of experience but also under changing conditions. Following Venkatesh and Davis's (2000) findings, we expected our predictions to hold over time. Therefore, we formally state:

H1a. At time 2: subjective norms will have a positive direct effect on behavioral intention.

H3a. At time 2: perceived usefulness will mediate the effect of subjective norms on behavioral intention.

H4a. At time 2: perceived ease of use will moderate the effect of perceived usefulness on behavioral intention.

H5a. At time 2: perceived ease of use will moderate the mediation of perceived usefulness in the effect of subjective norms on behavioral intention.

The research model is depicted in Figure 1.

The current research

To investigate our research hypotheses, we conducted a two-stage survey aiming at understanding user perception of a new technology's usefulness, ease of use and its acceptance

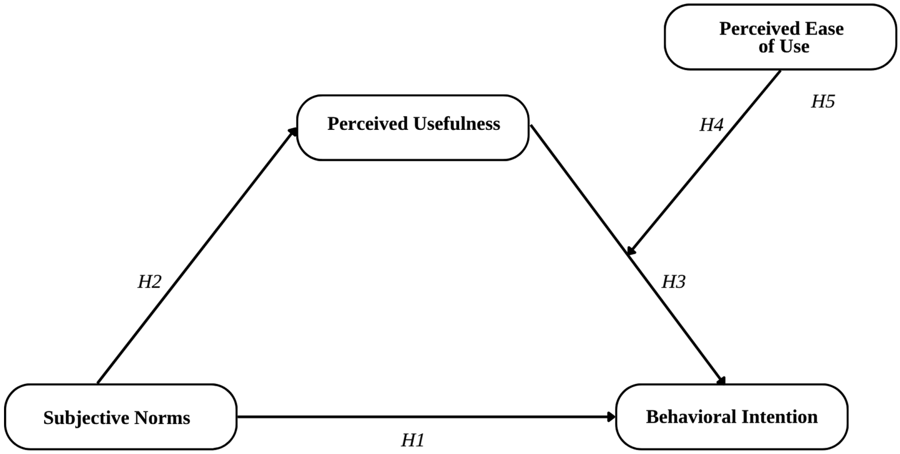

Figure 1. Research model

by others. Additionally, our study sought to assess user intention to initially adopt and continue using it over time. As COVID-19 social restrictions came into effect, we reached out to 269 Master of Business Administration (MBA) students, inviting them to complete a questionnaire regarding their recent experiences with a new technology. The pandemic created a unique context in which individuals were suddenly required to rely on digital solutions for communication, learning and productivity, often adopting technologies they had not previously used. This real-world shift presented a natural opportunity to study technology adoption under conditions of external pressure and urgency rather than choice. Subsequently, three months later, when COVID-19 guidelines were partially lifted and students had greater freedom in their daily routines, we conducted a follow-up study. This second measurement allowed us to assess whether participants continued to favor the use of the newly adopted technology once external constraints were reduced. The longitudinal design enabled us to examine both short-term adoption (during restriction) and sustained use (post-restriction), thereby providing insight into the role of contextual necessity in technology acceptance.

Surveying user attitude and perception regarding a technology that was recently adopted – time 1

Sample

A population of 184 MBA students accepted the invitation and participated in an online survey in exchange for course credit (M_age = 30.3, standard deviation (SD) = 5.68; 47.8% are females; 60.3% have an above-average income). The survey was conducted during the period of COVID-19 social restrictions.

Procedure and measurements

In this survey, participants were presented with a list of eight technology-related behaviors that were highly popular at the time, as displayed by the McKinsey report (April 2020). They were then asked to point to one technology-related behavior that they had recently engaged with for the first time. After that, participants answered questions regarding the technology-related behavior they had selected (see Supplementary_material_table_1 for the complete set of question items). Technologies that were initially adopted across this sample are presented in Supplementary_material_table_2.

SN: Participants were presented with a three-item SN scale, adapted from Venkatesh and Davis (2000). Specifically, they were asked to indicate on a seven-point scale (1 - not at all, 7 - very much) the extent to which they believed that most people think it is acceptable to use the new technology, the extent to which they believed the new technology was acceptable to others before COVID-19 and the extent to which they believed the new technology was not acceptable to others before COVID-19. These three items were correlated ($\alpha c = 0.684$); therefore, we averaged them into a single measure of SN.

PU: Participants were presented with a four-item PU scale and asked to rate their perception regarding the usefulness of the new technology (Davis, 1989). Specifically, they were asked to indicate on a seven-point scale (1 - not at all, 7 - very much) the extent to which they believed the new technology is a good way to perform a certain activity, the extent to which they believed the new technology is the fastest way to perform a certain activity, the extent to which they believed the new technology can save time and the extent to which they believed the new technology can save money. These four items were highly correlated ($\alpha c = 0.807$); therefore, we averaged them into a single measure of PU.

PEOU: Participants were presented with a two-item PEOU scale (Davis, 1989; Chau, 1996) and rated their perception of the new technology's ease of use. Specifically, they were asked to indicate on a seven-point scale (1 - not at all, 7 - very much) the extent to which they believed the new technology is simple to use and the extent to which they believed it would be easy for them to become skillful with the new technology. These two items were highly correlated ($rp = 0.844$); therefore, we averaged them into a single measure of PEOU.

BI: Participants were presented with three items regarding their future intention to use this new technology. Specifically, they were asked to indicate on a seven-point scale (1 - not at all, 7 - very much) the frequency they believed they would use this technology, the extent to which they believed they would pay for this technology in the future and the extent to which they believed they would use this technology in the future when COVID-19 restrictions would have been lifted (the latter item adapted from Davis, 1989; Chau, 1996).

Results

Basic correlation

A correlation analysis among research constructs revealed that in line with previous studies, these research findings supported the notion that at time 1, SN, PU and PEOU are positively correlated with BI (see Supplementary_material_table_3).

Main analysis

Mediation analysis. To test our predictions, we conducted a mediation analysis using the PROCESS bootstrapping method (Model 4, with 5,000 resamples; Hayes, 2013), examining whether PU mediated the relationship between SN and BI. In this analysis, the dependent variable was BI; SN was the independent variable (continuous measure) and PU was the mediator (continuous measure). In line with H3, the analysis confirmed the significant mediating role of PU ($\beta = 0.18$, *standard error (SE)* = 0.05; 95% CI: 0.0873 to 0.2864; $c\_ps = 0.30$). Specifically, in line with H2, SN increased PU ($\beta = 0.32$, $SE = 0.07$, 95% CI: 0.1781 to 0.4550), which, in turn, enhanced BI ($\beta = 0.55$, $SE = 0.07$; 95% CI: 0.4055 to 0.7005). Moreover, in line with H1, findings supported a direct effect of SN on BI ($\beta = 0.37$, $SE = 0.07$; 95% CI: 0.4055 to 0.7005). When adding PU to the model, this direct main effect remained significant ($\beta = 0.37$, $SE = 0.07$, 95% CI: 0.0887 to 0.2805), indicating a partial mediation effect of PU (H3) (see Table 1).

Moderated mediation analysis. Next, to examine whether SN led to PU and then to BI depending on PEOU levels, we conducted a moderated mediation analysis using the PROCESS bootstrapping method (Model 14, with 5,000 resamples; Hayes, 2013). We regressed BI on SN (continuous measure) as the predictor, with PU as the mediator and PEOU (continuous measure) as the moderator. Findings indicated a significant moderated mediation effect ($\beta = 0.36, SE = 0.07, p < 0.001$). In line with our predictions (H4, H5), results indicated

Table 1. Regression coefficients for mediation

Path analysis at time 1	
Perceived usefulness (mediator)	
Intercept	3.77* (0.31)
Subjective Norms	0.32* (0.07)
Behavioral intentions	
Intercept	−0.63* (0.42)
Subjective norms	0.36* (0.075)
Perceived usefulness	0.55* (0.075)
Cox-Snell or R^2	0.384*

Note(s): In the regression reported in the table, behavioral intention is the dependent variable The predictors are the PU and SN, continuous variables that take values from 1 to 7. Entries in the table represent unstandardized coefficients. Standard errors are reported in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

that the effect of PU significantly interacts with PEOU to influence BI ($\beta = 0.089$, $SD = 0.043$, $t = 2.087$, $p = 0.04$). Specifically, a floodlight analysis revealed that, when PEOU was higher than 2.93, PU significantly predicted BI (JN: $\beta = 0.28$, SE $= 0.14$, $t = 1.97$, $p = 0.05$), indicating that the effect of PU on BI depends on the level of PEOU. Consistent with this pattern, the indirect effect of SN on BI through PU is supported only at higher levels of PEOU, indicating moderated mediation. The direct effect of SN on BI remained significant, suggesting partial mediation (direct effect: $\beta = 0.36$, $SD = 0.07$, $t = 4.86$, $p = 0.000$) (see Table 2). The moderated mediation effect at time 1 is further represented in Supplementary_material_Figure_1.

Time 2 - surveying user attitude and perception regarding a technology three months after adoption

Sample

Three months after the initial data collection, we approached the participants from the first survey and requested their input in a single-item survey. Out of the 184 part-time MBA students who participated in the initial survey, 103 accepted the invitation and took part in the second online single-item survey. The survey was conducted during the period of enforced COVID-19 social restrictions.

Table 2. Moderated mediation analysis at time 1

	Behavioral intention
Intercept	1.227* (1.1)
SN Effect	0.359** (0.74)
PU Effect	0.020 (0.25)
PEOU Effect	−0.315 (0.19)
PU × PEOU	0.089* (0.042)
R^2	0.401**

Note(s): In the regression reported in the table, behavioral intention is the dependent variable. The predictors are the PU and PEOU, continuous variables that take values from 1 to 7. Entries in the table represent unstandardized coefficients. Standard errors are reported in parentheses. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.01$

Procedure and measurements

BI: In this survey, participants were reminded of the technology they had indicated as first adopted after the start of COVID-19 restrictions. Subsequently, participants were asked to rate on a seven-point scale (1 - not at all, 7 - very much) the extent to which they preferred to continue using the technology they had initially adopted and reported in the first survey. We correlated this data with the information we had collected at time 1 regarding SN, PU and PEOU.

Results

The correlation analysis indicates that participants' initial perception of SN and PU at Time 1 were positively associated with BI measured three months after technology adoption (SN: $rp = 0.384$, $p < 0.001$; PU: $rp = 0.448$, $p < 0.001$ (see Supplementary_material_table_4); Interestingly, the correlation between PEOU and BI was not stable over time. Specifically, findings indicate that the initial relationship between PEOU and BI diminished three months after adoption ($rp = 0.098$, $p > 0.1$). This is a crucial finding that may explain previous mixed results regarding the direct effect of PEOU on BI (see Supplementary_material_table_4).

Main analysis

Mediation analysis. To test our predictions, we conducted a second mediation analysis under the same method and parameters, examining whether PU mediated the relationship between SN and BI still at time 2. In this analysis, the dependent variable was BI at time 2; SN was the independent variable (continuous measure), and PU was the mediator (continuous measure). The analysis confirmed the significant mediating role of PU, ($\beta = 0.18$, $SE = 0.06$; 95% CI: 0.0751 to 0.3319; $c\_ps = 0.23$).

Specifically, in line with H2a, SN increased PU ($\beta = 0.37$, $SE = 0.091$, 95% CI: 0.1935 to 0.5557), which, in turn, enhanced BI ($\beta = 0.50$, $SE = 0.11$; 95% CI: 0.2758 to 0.7315). Moreover, in line with H1a, findings supported the direct effect of SN on BI at time 2 ($\beta = 0.29$, $SE = 0.11$; 95% CI: 0.0639 to 0.5155). This effect has remained significant when PU was added to the model, indicating its partial mediation effect (H3a) (see Table 3).

Moderated mediation analysis. To examine whether SN led to PU and then to BI depending on PEOU levels (H4a, H5a), we conducted a moderated mediation analysis using the PROCESS bootstrapping method (Model 14, with 5,000 resamples; Hayes, 2013). We regressed BI at time 2 on SN (continuous measure) as predictor, with PU as mediator and

Table 3. Regression coefficients for mediation

Path analysis at time 2	
Perceived usefulness (mediator)	
Intercept	3.56*** (0.40)
Subjective Norms	0.37*** (0.09)
Behavioral intentions	
Intercept	0.67 (0.62)
Subjective Norms	0.29* (0.011)
Perceived Usefulness	0.50*** (0.011)
Cox-Snell or R^2	0.2849*

Note(s): In the regression reported in the table, Behavioral Intention is the dependent variable The predictors are PU and SN, continuous variables that take values from 1 to 7. Entries in the table represent unstandardized coefficients. Standard errors are reported in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

PEOU (continuous measure) as moderator. Results demonstrated a significant moderated mediation effect ($\beta = 0.27$, $SE = 0.11$, $p < 0.05$). In line with the predictions, results indicated that the effect of PU significantly interacts with PEOU to influence BI ($\beta = 0.22$, $SE = 0.097$, $t = 2.252$, $p = 0.026$). Specifically, a floodlight (Johnson–Neyman) analysis revealed that PU significantly predicts BI only when PEOU exceeds 4.85 ($\beta = 0.31$, $SE = 0.16$, $t = 1.98$, $p = 0.05$). In contrast, at lower levels of PEOU, the effect of PU on BI was not significant. Consistent with this pattern, the indirect effect of SN on BI through PU is supported only at higher levels of PEOU, indicating moderated mediation. The direct effect of SN on BI remained significant ($\beta = 0.27$, $SE = 0.11$, $t = 2.38$, $p = 0.019$) (see Table 4). The moderated mediation effect at time 2 is further represented in Supplementary_material_Figure_2.

Discussion

Our research delved into the factors influencing users' adherence to a recently adopted technology. In our literature review, we encountered inconsistencies in the effects of the model constructs on BI, showing that some studies found that PU, PEOU and SN have a direct or indirect significant impact on BI, whereas others reported no significant effect of those constructs on BI (Kim *et al.*, 2009; Adnan *et al.*, 2025; Ursavaş *et al.*, 2025). To address these mixed findings, we introduced a novel approach that examined the interactions among those constructs, identifying conditions that enhance TAM's predictive power for BI. Surprisingly, we found that PEOU, previously considered a less influential variable (Legramante *et al.*, 2023; Yuliadewi *et al.*, 2024), plays a pivotal role within the TAM framework, setting the stage for more accurate predictions of BI.

Our findings indicate that PEOU moderates the impact of PU and SN on BI, with these constructs being more predictive when users perceive the new technology as easy to use. Conversely, when the new technology is perceived as difficult to use, TAM constructs demonstrated lower predictive power for BI. Importantly, after three months of usage, PEOU must be even higher to sustain continued use of the new technology.

Theoretical contributions

This work contributes to TAM research by exposing the important role of PEOU in predicting technology adoption. While numerous studies in this domain have primarily focused on examining how PEOU impacts PU or BI, our research takes a unique approach by delving into the intricate interactions among these constructs as they influence BI. Despite the multitude of variables explored as potential moderators in TAM research over the years (Acikgoz & Vega, 2022; Faqih, 2022), as far as we are aware, no prior study has investigated PEOU as a moderator in the context of TAM, nor have researchers previously presented the interaction

Table 4. Moderated mediation analysis of PEOU in the effect of PU on BI at time 2

	Behavioral intention
Intercept	7.42* (2.7)
SN Effect	0.27* (0.11)
PU Effect	−0.75 (0.59)
PEOU Effect	−1.18* (0.46)
PU × PEOU	0.22* (0.097)
R^2	0.33

Note(s): In the regression reported in the table, Behavioural Intention is the dependent variable. The predictors are the PU and PEOU, continuous variables that take values from 1 to 7. Entries in the table represent unstandardized coefficients
Standard errors are reported in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$

between PU and PEOU. Our use of mediated-moderation analysis has unveiled the pivotal role of PEOU in predicting user behavior. This deconstruction of the model represents a novel perspective and has the potential to illuminate the conflicting findings regarding the effects of TAM constructs on BI.

Practical implications

Our findings offer valuable insights for practitioners, underscoring the significance of prioritizing PEOU in technology development and marketing. If a given technology is not user-friendly, the influence of recommendations from friends or relatives and its PU are less significant within the consumer decision process.

Limitations and implications for further studies

While this study has yielded significant results, it is essential to acknowledge its limitations, which can serve as valuable pointers for future research. Firstly, the study was conducted under exceptional circumstances, with participants operating within the constraints of COVID-19 restrictions. These restrictions may have influenced participants' willingness to adopt technology required for communication and for daily activities.

Secondly, this research exclusively focused on TAM's core constructs: PU, PEOU and SN. In recent years, the research landscape has seen the exploration of numerous other variables, including experience, enjoyment and self-efficacy (Abdullah *et al.*, 2016) and perceived risk (Tsai, 2024), among others. Future studies could investigate the moderating role of PEOU in relation to these additional TAM constructs, as mentioned above. It is advisable for such studies to be conducted in conditions in which participants are not under the influence of social restrictions.

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Supplementary material

The supplementary material for this article can be found online

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Associate editor: Rafael Morais Pereira