# MOBILE MICRO-LEARNING ADOPTION AMONG ACCOUNTING STUDENTS

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## ABSTRACT

The pursuit of professional accounting designations necessitates rigorous engagement with complex regulatory frameworks, often concurrently with full-time employment. While Mobile Micro-learning offers a solution through ubiquitous access to bite-sized content, it simultaneously introduces the risk of cognitive fragmentation. Moving beyond contextual replication, this study integrates the Unified Theory of Acceptance and Use of Technology with the Value-based Adoption Model and Cognitive Load Theory. This theoretical synthesis allows for a rigorous evaluation of how extraneous cognitive load competes with perceived value in the high-stakes context of accounting education. Analyzing data from 342 Vietnamese accounting students via Structural Equation Modeling, the study identifies a critical tension between accessibility and concentration. The results demonstrate that while Ubiquity and Performance Expectancy are primary drivers of Perceived Value, Perceived Distraction and Information Risk serve as substantial barriers, significantly eroding the utility of mobile learning tools. Notably, Social Influence was found to have a non-significant effect, suggesting that students exhibit "academic individualism" when selecting tools for high-stakes exams. Furthermore, Perceived Value is established as a full mediator between these antecedents and the Intention to Adopt. These findings suggest that for high-stakes accounting education, the utility of "anytime, anywhere" learning is contingent upon mitigating the "always-on" nature of mobile interruptions.

**Keywords:** Mobile micro-learning, VAM, UTAUT, perceived value, perceived distraction, accounting education.

## INTRODUCTION

The contemporary accounting landscape is characterized by an escalating demand for technical proficiency and professional accreditation. For aspiring accountants, securing designations such as the Certified Public Accountant (CPA) or the Association of Chartered Certified Accountants (ACCA) is no longer merely an advantage but a requisite for career progression. This professionalization pressure forces students to absorb vast amounts of complex regulatory and financial standards, often while managing concurrent employment (Voshaar et al., 2023). As the digital era permeates higher education, the integration of mobile technology into this rigorous learning process has become inevitable, promising a shift from rigid classroom instruction to flexible, learner-centric models (Pajarito & Feria, 2016). Recent studies confirm that technology readiness is now a critical determinant of success in modern accounting curricula (Dwianto et al., 2024).

However, the transition to mobile-based learning presents a unique paradox in the context of accounting education. Traditional pedagogical tools are increasingly incongruent with the time-fragmented lifestyles of modern students. Mobile Micro-learning (MML) addresses this by fragmenting content into digestible units accessible anytime, a feature that recent systematic reviews identify as a primary driver of improved learning outcomes (Pedraja-Rejas et al., 2024). Yet, accounting is a discipline requiring deep cognitive processing and sustained attention. From the perspective of Cognitive Load Theory (CLT) (Sweller, 1988), mastering complex accounting standards imposes a high "intrinsic cognitive load" on learners. Consequently, the utilization of smartphones for such tasks introduces significant friction: the device intended to facilitate learning acts

as a source of "extraneous cognitive load" through digital distraction (Aagaard, 2015). Recent empirical evidence suggests that digital distractions significantly impair academic performance by fragmenting student attention, a phenomenon that remains persistent regardless of the learner's age or experience level (Choi & Yun, 2024). Consequently, students face a critical tension between the utility of "anytime access" and the cognitive cost of "fragmented attention."

Despite the proliferation of educational technology (EdTech) research, existing literature fails to adequately address this tension. The majority of studies utilize the Unified Theory of Acceptance and Use of Technology (UTAUT) to predict adoption, predominantly focusing on positive drivers such as performance and effort expectancy (Tian et al., 2024; Venkatesh et al., 2003). While recent scholarship has attempted to recontextualize UTAUT for higher education (Soares et al., 2025), there remains a scarcity of empirical research that simultaneously evaluates the negative externalities associated with mobile learning in high-stakes academic domains. Specifically, existing adoption models often overlook the cognitive dimension of these "sacrifices". While the benefits of mobile apps are documented, the detrimental impact of perceived distraction and information risk- viewed as cognitive costs that deplete limited working memory- remains underexplored (Balalle, 2024).

To bridge this gap and move beyond contextual replication, this study proposes a theoretical integration of UTAUT and CLT within the overarching framework of the Value-based Adoption Model (VAM) (Kim et al., 2007). Unlike standard adoption models, VAM posits that users are "value maximizers" who weigh benefits against sacrifices. By incorporating CLT, this research operationalizes these sacrifices not merely as inconveniences, but as cognitive barriers. Thus, adoption is framed as a trade-off between functional benefits (ubiquity, performance) and cognitive costs (distraction, risk). Accordingly, this study seeks to answer the following research questions:

1. How do the functional benefits of MML trade off against the cognitive sacrifices of distraction and risk?
2. To what extent does Perceived Value mediate the relationship between these antecedents and the intention to adopt MML for professional certification preparation?

## LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

### Mobile Micro-learning in Accounting

MML is defined as an educational approach that delivers content in small, specific, and manageable units via mobile devices, allowing learners to control the time and place of their study (Gikas & Grant, 2013). Unlike traditional e-learning, which often replicates long-form lectures in a digital format, MML is designed for "short bursts" of cognitive engagement -typically 2 to 15 minutes - making it particularly suitable for the scaffolding of complex concepts (Monib et al., 2025). In the context of accounting, this pedagogy involves breaking down monolithic standards (e.g., IFRS or GAAP) into modular components, such as bite-sized video explainers, digital flashcards for auditing assertions, or gamified quizzes for tax regulations.

Globally, the landscape of accounting education is undergoing a radical transformation driven by the integration of Artificial Intelligence (AI) and mobile ubiquity (Leong et al., 2021). Recent scholarship indicates that the "one-size-fits-all" model is obsolete. Higher education is shifting towards hyper-personalized learning environments where technology adoption is contingent on the tool's ability to provide immediate, context-aware feedback (Chen & Sitthiworachart, 2023; Soares et al., 2025). Furthermore, mobile learning significantly enhances critical thinking and learning outcomes, particularly when integrated with adaptive learning algorithms that tailor content difficulty to the student's proficiency level (Pedraja-Rejas et al., 2024; Peng & Wang, 2025; Steinbacher & Hoffmann, 2015).

In the accounting profession, where continuous professional development is mandatory, MML has become the preferred modality for exam preparation (e.g., CPA, CFA, ACCA). Dwianto et al. (2024) highlight that technology readiness regarding AI-based tools is now a critical predictor of adoption among accounting students. The global trend is moving towards "Intelligent Micro-learning," where apps not only deliver content but also predict knowledge gaps, thereby optimizing the study efficiency for high-stakes certifications (Salleh et al., 2023).

The adoption of MML in Vietnam presents a unique and compelling case study. Vietnam is currently experiencing a rapid digital transformation in its education sector, fueled by a high smartphone penetration rate and a young demographic of "digital natives." In addition, the Vietnamese Ministry of Finance has laid out a roadmap for the full adoption of International Financial Reporting Standards (IFRS) by 2025. This creates immense pressure on accounting students and professionals to update their knowledge base rapidly, rendering traditional, static textbooks insufficient. MML apps offer the agility to update content in real-time, matching the dynamic nature of these regulatory changes. While Vietnamese students are highly receptive to EdTech, the cultural context of ubiquitous connectivity poses challenges (Anh & Linh, 2023). A recent study by Nguyen et al. (2022) on e-learning in Vietnam suggests that while access to technology is high, self-regulated learning capabilities often lag, leading to ineffective usage. Moreover, in Vietnam, mobile phones are the primary access point for the internet for many students. However, this reliance means the learning device is also the primary social and entertainment device. This convergence exacerbates the "distraction" factor, a core variable in this study. The tension is palpable: Vietnamese accounting students need MML to master the new IFRS standards efficiently, yet the very ecosystem of the Vietnamese mobile internet is saturated with social media interruptions (TikTok, Zalo, Facebook), creating a high-risk environment for cognitive distraction.

## Theoretical Integration: UTAUT, VAM, and CLT

While the UTAUT model (Venkatesh et al., 2003; Tian et al., 2024) effectively explains technological fit through positive determinants (e.g., Performance and Effort Expectancy), its inherent "pro-innovation bias" often overlooks the non-monetary costs critical in high-stakes contexts like accounting education. To address this, this study integrates UTAUT with the Value-based Adoption Model (VAM) (Kim et al., 2007) and Cognitive Load Theory (CLT) (Sweller, 1988).

Within this synthesized framework, Perceived Value (PV) acts as the central cognitive filter balancing two opposing forces:

1. *Benefits (Drivers):* Rooted in UTAUT and adapted for mobile environments (Soares et al., 2025), these include Performance Expectancy, Effort Expectancy, Social Influence, and Ubiquity.
2. *Sacrifices (Barriers):* Viewed through the lenses of VAM and CLT, the costs in Mobile Micro-Learning are cognitive rather than monetary. Perceived Distraction (Aagaard, 2015; Choi & Yun, 2024) and Perceived Information Risk represent "extraneous cognitive load" that depletes the limited working memory required for complex accounting tasks.

Drawing on Value Theory (Zeithaml, 1988), we posit that technical utility alone cannot drive adoption in precision-oriented fields. Accounting students act as rational "value maximizers" who will only adopt MML if the marginal functional benefits outweigh the cognitive sacrifices. Thus, within this comprehensive Benefit-Risk framework, minimizing cognitive inhibitors is just as imperative as maximizing technical drivers.

## The Benefits and Perceived Value

### Performance Expectancy and Perceived Value

Within the UTAUT framework, Performance Expectancy (PE) is defined as the degree to which an individual believes that using the system will help them attain gains in job performance (Venkatesh et al., 2003). When integrated with the VAM, PE is conceptualized as the primary "utilitarian benefit." VAM posits that users are rational actors who assess value based on a "get-versus-give" component. In this equation, PE represents the cognitive assessment of "what I get" (instrumental utility) relative to the goal of the activity (Kim et al., 2007). In the specific context of accounting education, the "job performance" metric is quantifiable and high-stakes: passing professional certification examinations and mastering complex financial standards. Accounting students operate under severe time constraints. Therefore, if a MML application can demonstrate that it accelerates knowledge retention or improves the probability of passing an exam, the learner perceives this utility as a direct translation to "Value." The app is not judged on entertainment, but on its efficacy as a career-advancement tool.

Extensive literature establishes PE as the primary driver of Perceived Value (PV) in mobile and educational technology adoption (Kim et al., 2007; Qashou, 2021; Yuca & Dabaj, 2025). Specifically within the accounting domain, students heavily prioritize functional capabilities that directly improve learning success and solve complex problems (Dwianto et al., 2024; Voshaar et al., 2023). Recent studies further characterize modern learners as "strategic," evaluating digital tools almost exclusively based on their efficiency in delivering tangible academic outcomes (Owan et al., 2025; Sergeeva et al., 2025; Soares et al., 2025; Tian et al., 2024). Consequently, if accounting students perceive that MML applications enhance their study efficiency and exam preparedness, their assessment of the app's overall value will significantly increase.

*H1:* Performance Expectancy has a positive effect on the Perceived Value of Mobile Micro-learning.

### Effort Expectancy and Perceived Value

Effort Expectancy (EE) is derived from the "Ease of Use" construct in the Technology Acceptance Model (TAM) and is a core component of UTAUT. It represents the degree of ease associated with the use of the system (Venkatesh et al., 2003). In the context of VAM, EE is considered a non-monetary cost reduction. Cognitive Load Theory (Sweller, 1988) supports this by suggesting that human working memory is limited. If an interface is difficult to navigate, it imposes "extraneous cognitive load," stealing mental resources away from the actual learning material. Conversely, a high EE reduces this load, thereby increasing the PV of the learning session. Accounting is an inherently complex discipline, characterized by dense regulatory texts and multi-step calculations. Students preparing for professional certifications are already operating at maximum cognitive capacity. If a mobile app requires complex navigation, slow loading times, or non-intuitive gestures, the "cost of effort" becomes too high. An app with high EE acts as a "frictionless" conduit. For a busy accounting student, the ability to access a tax quiz in two taps (low effort) translates directly into value because it fits seamlessly into the "micro-moments" of their day.

Foundational research establishes EE as a critical determinant of PV, particularly in mobile environments where hardware constraints make usability a strict precondition for utility (Kim et al., 2007; Sagnier et al., 2020; Venkatesh et al., 2003). Recent studies in EdTech and accounting contexts corroborate this dynamic, demonstrating that steep learning curves and difficult navigation frequently lead to the rejection of digital tools, regardless of their potential functional benefits (Dwianto et al., 2024; Monib et al., 2025; Tian et al., 2024). Therefore, this study posits that the easier a mobile accounting application is to use, the less "cognitive tax" the student pays, directly resulting in a higher PV.

*H2:* Effort Expectancy has a positive effect on the Perceived Value of Mobile Micro-learning.

### Social Influence and Perceived Value

Social Influence (SI) is defined in the UTAUT framework as the degree to which an individual perceives those important others believe they should use the new system (Venkatesh et al., 2003). When integrated into the VAM, SI is not merely a source of normative pressure; it acts as a signal of "Social Value" or symbolic utility. According to Signaling Theory (Spence, 1973), the adoption of a technology endorsed by a high-status reference group (such as successful CPAs or top-ranking students) confers a perception of legitimacy and quality upon the tool, thereby enhancing its perceived value in the eyes of the potential adopter. The accounting profession is deeply communal and hierarchical. Students preparing for high-stakes certifications often operate in tight-knit cohorts or study groups where "fear of missing out" is prevalent. If a specific MML app is recommended by a respected lecturer or is widely used by peers passing their exams, the app is no longer just a tool; it becomes a "standard" for success. The value here is derived from risk reduction and belonging. By using what "successful others" use, the student perceives the app as valuable because it aligns them with professional norms and reduces the anxiety of choosing the wrong study method.

Research establishes SI as a critical heuristic for assessing the value of digital tools, where peer endorsement serves as a reliable proxy for quality assurance and perceived utility (Tian et al., 2024; Venkatesh et al.,

2003). Particularly in the demanding context of accounting education and modern digital networks, students rely heavily on behavioral cues from their cohort and professional community standards to navigate complex curricula (Dwianto et al., 2024; Soares et al., 2025). Therefore, this research posits that positive reinforcement and established norms within the accounting community validate the effectiveness of MML applications, directly increasing their PV.

*H3:* Social Influence has a positive effect on the Perceived Value of Mobile Micro-learning.

### Ubiquity and Perceived Value

Ubiquity (UBI) refers to the ability to access information unconstrained by time and space. While not part of the original UTAUT, it is the defining characteristic of Mobile learning and a core construct in mobile-specific VAM studies (Kim et al., 2007). In the context of "Time-Space Distantiation" theory (Giddens, 1984), ubiquity allows learning to be "lifted out" of the physical classroom and re-embedded into the student's daily life. For accounting certification candidates, "Time" is the scarcest resource. Most are working professionals or final-year students with rigid schedules. Traditional learning requires dedicated blocks of time. UBI allows for opportunistic learning. This flexibility transforms "dead time" into "productive time." The value here is not just in the content, but in the availability of the content. Being able to review Audit Standards on a smartphone while queuing at a bank creates immense instrumental value that a desktop computer or textbook cannot provide.

Empirical research identifies UBI as a paramount predictor of PV in mobile learning, as "anytime, anywhere" portability is essential for delivering bite-sized content and sustaining self-regulated engagement (Jomah et al., 2017; Kim et al., 2007; Pedraja-Rejas et al., 2024). Post-pandemic, this flexibility has evolved from a mere advantage into a non-negotiable expectation (Soares et al., 2025). Specifically in accounting education, UBI enables the opportunistic, "on-the-go" practice vital for mastering complex subjects (Voshaar et al., 2023). By offering this unique flexibility lacking in traditional formats, UBI significantly drives the overall PV of MML applications.

*H4:* Ubiquity has a positive effect on the Perceived Value of Mobile Micro-learning.

## The Sacrifices and Perceived Value

### Perceived Information Risk and Perceived Value

Perceived Risk Theory (PIR), originally conceptualized by Bauer (1960), defines risk as the uncertainty and potentially adverse consequences associated with a consumer's action. When integrated into the VAM, PIR is classified as a critical "Sacrifice." It represents the non-monetary cost of uncertainty. Unlike performance risk (the app failing to work), PIR in an educational context refers to the learner's apprehension that the content provided may be inaccurate, outdated, or incomplete. According to the cognitive trade-off calculus of VAM, any increase in perceived risk acts as a "psychological tax," directly subtracting from the overall PV of the technology (Kim et al., 2007). In accounting education, the tolerance for error is virtually zero. The discipline is governed by rigid, frequently changing frameworks (e.g., IFRS updates, tax law amendments). A MML app might offer excellent convenience, but if a student suspects that the tax rates in a quiz are from 2024 instead of 2025, the utility of the app collapses. For a student preparing for a CPA exam, learning incorrect information is worse than learning nothing at all, as it requires "unlearning" and relearning. Therefore, the fear (risk) that the app provides "bad data" creates a substantial barrier, leading the student to devalue the app regardless of its other features.

Foundational theories establish PIR as a potent psychological barrier that directly diminishes PV (Featherman & Pavlou, 2003; Kim et al., 2007). In educational settings, learners exhibit a famously low tolerance for inaccuracy; even minor deficiencies in information quality or skepticism toward digital content reliability can precipitate significant drops in trust and perceived utility (Almaiah et al., 2016; Salih et al., 2025). This sensitivity is acutely exacerbated in the precision-oriented domain of accounting, where the consequences

of relying on erroneous data are severe, making information quality a critical antecedent to user acceptance (Fitriat et al., 2023). Given the high stakes of professional accounting examinations, this study posits that the fear of inaccurate content constitutes a significant sacrifice, substantially reducing the learning tool's overall value.

*H5:* Perceived Information Risk has a negative effect on the Perceived Value of Mobile Micro-learning.

### Perceived Distraction and Perceived Value

Within the VAM framework, Perceived Distraction (PD) constitutes a significant non-monetary "Sacrifice," deeply rooted in Cognitive Load Theory (Sweller, 1988). PD refers to the extent to which a user's attention is diverted from the primary learning task by extraneous stimuli inherent to the device, such as notifications, social media alerts, or interface clutter. This phenomenon triggers the "split-attention effect," compelling the brain to engage in rapid context switching. The metabolic and temporal cost incurred to re-establish focus after each interruption - known as the "switching cost" - reduces the cognitive resources available for information processing, thereby diminishing the utility and overall PV of the learning tool. For accounting students, the mastery of subject matter requires "Deep Work" and sustained concentration. Solving complex financial reporting problems or reconciling audit evidence involves holding multiple variables in working memory simultaneously. While MML offers the benefit of UBI, the mobile device is inherently a "weapon of mass distraction," where the learning application competes for attention with high-dopamine alternatives like TikTok or Instagram. If the "cognitive tax" of resisting distraction or recovering from interruptions is too high, the student perceives the app as inefficient. Instead of a tool for productivity, it becomes a source of frustration. The rational learner will thus conclude that the sacrifice outweighs the benefit, leading to a negative valuation of the technology.

Recent empirical evidence strongly links digital distraction to reduced efficacy in cognitively demanding learning environments. Extraneous mobile stimuli and multitasking induce detrimental "cognitive load" and "cognitive fatigue," severely degrading recall, academic performance, and intrinsic motivation (Ali & Saher, 2025; Chen et al., 2025). Furthermore, the omnipresence of these interruptions disrupts cognitive "flow," acting not merely as a behavioral issue but as a systemic barrier and environmental design flaw that significantly diminishes user satisfaction and perceived utility (Pedraja-Rejas et al., 2024; West, 2025). Consequently, this study posits that perceived distraction acts as a powerful psychological inhibitor, substantially reducing the net value derived from the mobile learning experience.

*H6:* Perceived Distraction has a negative effect on the Perceived Value of Mobile Micro-learning.

## Perceived Value and Intention to Adopt Mobile Micro-learning

In the VAM, PV is the overarching construct that determines behavioral intention. Unlike the TAM, which assumes a direct path from utility to intention, VAM draws upon Rational Choice Theory. It posits that individuals are "value maximizers" who perform a mental calculus: they weigh the total benefits (EE, PE, UBI, SI) against the total sacrifices (PIR, PD). The resulting "net value" is the sole immediate predictor of the Intention to Adopt (INT). If the PV is positive, the intention to use the technology is formed; if negative, the technology is rejected, regardless of how advanced it may be (Kim et al., 2007). For accounting students, time is an asset with a high opportunity cost. The decision to adopt a MML application is effectively an investment decision. These students intuitively apply a "Net Present Value" mindset to their study tools. They ask: "Does the return on this app (passing the CPA exam) exceed the cost (time spent, frustration, risk of error)?" PV acts as the decision gatekeeper. A student might acknowledge an app is "cool" (SI) and "easy" (EE), but if the overall Value is perceived as low (e.g., due to high Distraction), they will not form the intention to use it. Conversely, a high PV creates a compelling "bargain" that drives the conscious plan to integrate the app into their daily study routine.

The predictive primacy of PV on behavioral intention is robustly supported by contemporary research on educational technologies, which shows that "net benefit" serves as the primary motivational trigger for adoption (Al-Abdullatif, 2023; Tian et al., 2024; Trapero et al., 2019). Furthermore, recent empirical evidence, including studies within the Vietnamese context, confirms that post-pandemic learners aggressively filter digital tools based on their capacity to deliver tangible overall benefits rather than just individual features (Le et al., 2025; Soares et al., 2025). Thus, the following hypothesis is formulated:

*H7:* Perceived Value has a positive effect on the Intention to Adopt Mobile Micro-learning.

## The Mediating Role of Perceived Value

The differentiating factor of the VAM compared to standard acceptance models (like TAM or UTAUT) is that technical attributes (such as PE or UBI) or psychological costs (such as PIR or PD) do not directly compel a user to adopt a system. Instead, these factors act as input variables for a "mental calculation" of net worth. Consequently, the antecedents only influence the INT indirectly, via their impact on the user's perception of value (Kim et al., 2007). Accounting students are strategic decision-makers operating under resource constraints. They do not adopt a mobile app simply because it is easy to use (H2) or socially popular (H3). A student may acknowledge that an app is easy to navigate (EE). However, if that ease of use does not translate into a perceived "worth" (PV) for their exam preparation, they will not form an intention to use it. Similarly, the presence of PIR (H5) does not automatically stop adoption; it lowers the PV. If the value remains positive despite the risk, adoption may still occur. Thus, PV explains why drivers lead to action and why barriers hinder it. It is the necessary bridge between attribute and behavior.

Scholarship in information systems and behavioral psychology provides robust evidence for the mediating centrality of PV. It is widely established that while quality factors are essential, they are merely antecedents that must be converted into a value judgment to influence behavioral intention (Kim et al., 2007). Contemporary research on AI and digital tool adoption in higher education validates that constructs like PE and SI do not trigger adoption in isolation; they must first generate a perception of "net benefit" to drive the intention to use, reinforcing the status of PV as the proximal determinant of behavior (Tian et al., 2024; Trapero et al., 2019). Accordingly, this study hypothesizes that:

*H8a:* Perceived Value mediates the relationship between Performance Expectancy and Intention to Adopt.

*H8b:* Perceived Value mediates the relationship between Effort Expectancy and Intention to Adopt.

*H8c:* Perceived Value mediates the relationship between Social Influence and Intention to Adopt.

*H8d:* Perceived Value mediates the relationship between Ubiquity and Intention to Adopt.

*H8e:* Perceived Value mediates the relationship between Perceived Information Risk and Intention to Adopt.

*H8f:* Perceived Value mediates the relationship between Perceived Distraction and Intention to Adopt.

While VAM posits that value maximizes the intention to adopt, classical UTAUT suggests direct pathways. Therefore, following the mediation analysis procedures (Preacher & Hayes, 2008), this study assumes a mediation framework but will explicitly test direct paths to determine whether PV acts as a full or partial mediator.

## METHODOLOGY

### Research Design

This study adopts a quantitative research design using a deductive approach to validate the proposed research model. A cross-sectional survey method was employed to test the hypotheses. This approach is deemed appropriate for investigating the relationships between antecedents (Benefits and Sacrifices) and the Intention to Adopt MML within the specific context of accounting education.

### Data Collection and Sample

The population for this study consists of undergraduate students majoring in Accounting and Auditing at universities in Vietnam. This group was selected because accounting students face high-pressure certification requirements (e.g., CPA, ACCA) that make efficient, time-saving learning tools particularly relevant. Data was collected using a non-probability convenience sampling technique between September 2025 and November 2025. To maximize reach and ensure a comprehensive representation of the target population, a mixed-mode data collection strategy was employed, utilizing both online and offline channels. Online surveys were distributed via popular instant messaging platforms widely used by Vietnamese students (e.g., Zalo, Facebook Messenger), specifically targeting dedicated accounting study groups, academic forums, and professional certification networks. This was supplemented by the in-person distribution of paper-based questionnaires at the campuses of 4 major universities offering robust accounting programs in Hanoi, Vietnam. While convenience sampling is a non-probability method, targeting these specific academic networks and physical campuses ensured that the respondents accurately reflected the population of interest: accounting students actively engaged in rigorous academic preparation. Responses from the paper-based surveys were manually digitized and combined with the online dataset. To ensure data quality, all responses were rigorously screened for missing values, unengaged response patterns (e.g., straight-lining), and potential duplicate submissions across the two collection modes.

Out of 369 responses received, 27 were excluded due to failing the screening questions (i.e., lacking awareness of mobile learning applications) or exhibiting unengaged response patterns (e.g., straight-lining). Consequently, a final sample of 342 valid responses was retained for analysis, yielding a valid response rate of approximately 92.68%. This sample size exceeds the recommended minimum of 200 for SEM to ensure stable maximum likelihood estimation (Kline, 2011). Furthermore, it satisfies the robust observation-to-item ratio of at least 10:1 (Bentler & Chou, 1987), providing adequate statistical power to detect medium effect sizes.

### Measurement Instrument

The survey instrument was developed by adapting validated scales from prior literature to fit the specific context of MML in accounting. All items were measured using a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Given that the original measurement scales were developed in English, a rigorous double-blind back-translation procedure (Brislin, 1970) was employed to translate the items into Vietnamese, ensuring semantic equivalence and cultural appropriateness. Subsequently, the draft questionnaire was reviewed by a panel of 3 academic experts in accounting education and information systems to establish content validity. Based on their feedback, minor adjustments were made to the wording to align with the specific context of high-stakes accounting exams in Vietnam.

Prior to the main data collection, a pilot test was conducted with 30 undergraduate accounting students. The pilot results confirmed that all items were clear, unambiguous, and possessed adequate initial reliability (Cronbach's alpha > 0.70).

**Table 1.** Measurement Items and Sources

| Construct | Code | Measurement Item | Source |
|---|---|---|---|
| Performance Expectancy (PE) | PE1 | Using MML apps helps me improve my grades in accounting subjects. | Venkatesh et al. (2003); Tian et al. (2024) |
| | PE2 | MML allows me to pass accounting certification exams more effectively. | |
| | PE3 | Using MML increases my productivity in studying complex tax/audit standards. | |
| | PE4 | I find MML useful for memorizing accounting formulas and regulations. | |
| | PE5 | Overall, MML is a useful tool for my professional development. | |
| Effort Expectancy (EE) | EE1 | Learning to operate the MML app is easy for me. | Venkatesh et al. (2003); Dwianto et al. (2024) |
| | EE2 | The interaction with the MML app is clear and understandable. | |
| | EE3 | It is easy for me to find the specific accounting topic I need in the app. | |
| | EE4 | I can become skillful at using the MML app without much effort. | |
| Social Influence (SI) | SI1 | People who are important to me (e.g., lecturers, mentors) think I should use MML. | Venkatesh et al. (2003); Soares et al. (2025) |
| | SI2 | People who influence my behavior (e.g., successful senior students) use MML. | |
| | SI3 | The accounting faculty/university supports the use of MML for studying. | |
| | SI4 | Using MML is considered a trend among high-performing accounting students. | |
| Ubiquity (UBI) | UBI1 | I can use MML to study accounting anytime and anywhere. | Kim et al. (2007); Voshaar et al. (2023) |
| | UBI2 | MML allows me to utilize my spare time effectively for revision. | |
| | UBI3 | The MML app provides learning access regardless of my location. | |
| | UBI4 | MML eliminates the time and place constraints of traditional studying. | |
| | UBI5 | It is convenient to access accounting quizzes on the go. | |
| Perceived Information Risk (PIR) | PIR1 | I worry that the accounting information in the app may be outdated (e.g., old tax rates). | Featherman & Pavlou (2003); |
| | PIR2 | I am concerned that the app might provide incorrect solutions to accounting problems. | |
| | PIR3 | There is a high risk that the content does not align with official exam standards. | |
| | PIR4 | I feel uncertain about the accuracy of the learning materials provided by the app. | |
| Perceived Distraction (PD) | PD1 | Notifications on my phone distract me while I am trying to study on the app. | Chen et al. (2025); Pedraja-Rejas et al. (2024) |
| | PD2 | It is hard to maintain deep concentration on accounting problems when using a mobile device. | |
| | PD3 | I often switch to social media apps while I am supposed to be learning on the MML app. | |
| | PD4 | Using the mobile app fragments my attention span. | |
| | PD5 | The small screen and interface clutter make it difficult to focus on complex tasks. | |
| Perceived Value (PV) | PV1 | Using MML offers good value for the time and effort I spend. | Kim et al. (2007); Zeithaml (1988); Le et al. (2025) |
| | PV2 | Compared to the effort I put in, the learning outcome from MML is beneficial. | |
| | PV3 | MML provides a good bargain in terms of learning efficiency. | |
| | PV4 | I feel that using MML is a wise choice for my accounting studies. | |
| Intention to Adopt (INT) | INT1 | I intend to use MML for my accounting studies in the future. | Venkatesh et al. (2003); |
| | INT2 | I predict I will use MML frequently for exam preparation. | |
| | INT3 | I plan to use MML as a primary tool for revising accounting standards. | |
| | INT4 | I will recommend MML apps to other accounting students. | |

## Common Method Bias Assessment

Given that the data were collected using a cross-sectional, self-reported survey, Common Method Bias (CMB) was considered a potential risk (Podsakoff et al., 2003). To mitigate this, both procedural and statistical remedies were implemented. Procedurally, respondents were assured of strict anonymity and confidentiality. The survey instructions explicitly stated that there were no right or wrong answers, encouraging honest responses. Furthermore, the order of the items was randomized to prevent pattern-driven answering.

Statistically, Harman's Single-Factor test was conducted using SPSS. The unrotated principal component factor analysis revealed that the first single factor accounted for only 24.307% of the total variance, which is significantly below the recommended threshold of 50%. This result confirms that CMB is not a pervasive issue in this dataset and does not confound the interpretation of the structural relationships.

## Data Analysis Method

The data analysis will be conducted using SEM, specifically utilizing AMOS software. SEM is chosen because of its ability to simultaneously estimate the measurement model (relationships between items and constructs) and the structural model (relationships between constructs), which is essential for testing the mediating role of PV (Hypothesis H8). The analysis will follow the two-step approach recommended by Anderson and Gerbing (1988):

1. Measurement Model Assessment: Evaluating the reliability and validity of the constructs using Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).
2. Structural Model Assessment: Testing the hypothesized relationships (path coefficients), the explanatory power of the model (R2), and the model fit indices (e.g., CFI, RMSEA, SRMR).

Prior to testing the hypotheses, this study assessed the measurement instrument's psychometric properties. As summarized in Table 2, the results indicate a robust measurement model:

All individual item loadings ranged from 0.710 to 0.835. These values exceed the recommended threshold of 0.70 and are statistically significant ($p < 0.001$), demonstrating that the items serve as strong indicators for their respective constructs (Hair et al., 2010).

The Cronbach's Alpha coefficients for all constructs ranged from 0.865 (for UBI) to 0.898 (for PV), well above the acceptable limit of 0.70. Similarly, the CR values were all above 0.86, confirming excellent internal consistency. The AVE for all constructs ranged from 0.569 to 0.636, surpassing the 0.50 threshold. This confirms that the latent constructs explain more than half of the variance of their indicators (Fornell & Larcker, 1981).

**Table 2.** Factors loading, Cronbach's Alpha, Reliability and Convergent Validity

| Factors | Items | Cronbach's Alpha | Factor loadings | CR | AVE |
|---|---|---|---|---|---|
| Performance Expectancy (PE) | PE1 | 0.863 | 0.725 | 0.864 | 0.559 |
| | PE 2 | | 0.748 | | |
| | PE 3 | | 0.879 | | |
| | PE4 | | 0.821 | | |
| | PE 5 | | 0.813 | | |
| Effort Expectancy (EE) | EE1 | 0.845 | 0.783 | 0.846 | 0.579 |
| | EE 2 | | 0.827 | | |
| | EE 3 | | 0.841 | | |
| | EE 4 | | 0.857 | | |
| Social Influence (SI) | SI1 | 0.856 | 0.830 | 0.857 | 0.600 |
| | SI2 | | 0.820 | | |
| | SI3 | | 0.820 | | |
| | SI4 | | 0.853 | | |

| | | | | | |
|---|---|---|---|---|---|
| Ubiquity (UBI) | UBI1 | 0.863 | 0.773 | 0.862 | 0.558 |
| | UBI2 | | 0.846 | | |
| | UBI3 | | 0.787 | | |
| | UBI4 | | 0.806 | | |
| | UBI5 | | 0.790 | | |
| Perceived Information Risk (PIR) | PIR1 | 0.832 | 0.852 | 0.831 | 0.553 |
| | PIR2 | | 0.818 | | |
| | PIR3 | | 0.780 | | |
| | PIR4 | | 0.806 | | |
| Perceived Distraction (PD) | PD1 | 0.840 | 0.842 | 0.841 | 0.517 |
| | PD2 | | 0.726 | | |
| | PD3 | | 0.759 | | |
| | PD4 | | 0.797 | | |
| | PD5 | | 0.777 | | |
| Perceived Value (PV) | PV1 | 0.867 | 0.877 | 0.868 | 0.621 |
| | PV2 | | 0.796 | | |
| | PV3 | | 0.870 | | |
| | PV4 | | 0.825 | | |
| Intention to Adopt (INT) | INT1 | 0.844 | 0.814 | 0.847 | 0.582 |
| | INT2 | | 0.760 | | |
| | INT3 | | 0.835 | | |
| | INT4 | | 0.885 | | |

Discriminant validity was assessed using the Fornell-Larcker criterion. This criterion posits that the square root of the AVE for each construct should be greater than its highest correlation with any other construct in the model.

As shown in Table 4, the square roots of the AVEs (represented by the bold values on the diagonal, ranging from 0.754 to 0.798) are consistently higher than the off-diagonal inter-construct correlations. The highest correlation observed is between PE and PV (r = 0.633), which is well below the square root of AVE for both constructs. Furthermore, all correlation coefficients are below the threshold of 0.85, indicating that multicollinearity is not a concern.

Notably, the negative correlations between the "sacrifice" factors (PIR and PD) and the "benefit" factors (e.g., PV, INT) align with the theoretical expectations of the VAM.

**Table 3.** Correlation coefficient among core variables

| | PE | PD | UBI | PIR | EE | SI | PV | INT |
|---|---|---|---|---|---|---|---|---|
| PE | 0.748 | | | | | | | |
| PD | -0.191** | 0.719 | | | | | | |
| UBI | 0.331*** | 0.007 | 0.747 | | | | | |
| PIR | -0.187** | 0.429*** | -0.140* | 0.743 | | | | |
| EE | 0.351*** | -0.175** | 0.305*** | -0.195** | 0.761 | | | |
| SI | 0.314*** | -0.085 | 0.381*** | -0.121† | 0.244*** | 0.774 | | |
| PV | 0.633*** | -0.384*** | 0.472*** | -0.447*** | 0.521*** | 0.335*** | 0.788 | |
| INT | 0.409*** | -0.183** | 0.366*** | -0.216** | 0.206** | 0.231*** | 0.584*** | 0.763 |

## RESULTS

### Demographic Profile of Respondents

The descriptive statistics of the respondent profile are presented in Table 4. The final sample consists of 342 valid responses collected from undergraduate students majoring in Accounting and Auditing. As shown in the table, the gender distribution reflects the typical composition of accounting cohorts, with a predominance of female students (64.91%) compared to male students (35.09%). Regarding academic seniority, the sample is well-distributed across all four years, with a slight concentration in the junior and senior years (Year 3: 35.09%; Year 4: 25.15%). This distribution is advantageous for the study, as 3rd and 4th-year students are closer to professional certification exams, making them more likely to assess the PV of learning tools critically. A significant characteristic of this sample is the high level of mobile device engagement. The majority of respondents (71.64%) reported using their smartphones for more than 4 hours per day. This data confirms that the respondents belong to a "digital native" generation (Gen Z), ensuring they possess the necessary technological literacy to provide reliable feedback on MML adoption.

**Table 4.** Demographic Profile of Respondents (N=342)

| Characteristic | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 120 | 35.09% |
| | Female | 222 | 64.91% |
| Year of Study | First Year | 51 | 14.91% |
| | Second Year | 85 | 24.85% |
| | Third Year | 120 | 35.09% |
| | Fourth Year | 86 | 25.15% |
| Average Daily Mobile Usage | Less than 2 hours | 15 | 4.39% |
| | 2 – 4 hours | 82 | 23.98% |
| | 4 – 6 hours | 145 | 42.40% |
| | More than 6 hours | 100 | 29.24% |

### Data Screening and Assumption Checks

Prior to conducting the empirical analysis, the dataset was rigorously screened to ensure data quality and validate the underlying assumptions of SEM. First, regarding missing data handling, the online survey utilized a forced-response mechanism, preventing incomplete submissions. For the digitized paper-based responses, any questionnaires with missing values or unengaged response patterns (e.g., straight-lining) were excluded using listwise deletion during the initial data cleaning phase. This rigorous screening process resulted in the final dataset of 342 valid responses.

Second, the assumption of univariate normality was evaluated by examining the skewness and kurtosis of all measurement items. The results demonstrated that the skewness values ranged from -1.080 to 0.407, and the kurtosis values ranged from -0.900 to 0.771. Because all values fell well within the widely accepted thresholds of ±3 for skewness and ±10 for kurtosis (Hair et al., 2010; Kline, 2011), the data distribution was deemed sufficiently normal for maximum likelihood estimation. Furthermore, potential multivariate outliers were assessed, and no significant influential cases that could distort the structural relationships were detected. Therefore, the dataset met all necessary criteria to proceed with the measurement and structural model assessments.

### Structural Model and Hypothesis Testing

#### Assessment of Structural Model Fit

Before testing the specific hypotheses, the overall goodness-of-fit of the structural model was evaluated to ensure that the theoretical model adequately represents the observed data. Following the recommendations

of Hair et al. (2010) and Hu and Bentler (1999), multiple fit indices were examined, including Chi-square normalized by degrees of freedom (CMIN/DF), Goodness of Fit Index (GFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA).

The results of the structural model analysis are summarized in Table 5. The analysis yielded a CMIN/DF of 1.310, which falls well within the ideal range of 1 to 3, indicating a strong model parsimony. Regarding the incremental fit indices, both the CFI (0.970) and TLI (0.967) significantly exceeded the recommended threshold of 0.90, confirming that the specified model offers a substantial improvement over the baseline independence model. Furthermore, the absolute fit indices also demonstrated an excellent fit. The RMSEA value was 0.030, which is below the stringent cutoff of 0.05, suggesting a "close fit." The GFI was recorded at 0.898, effectively meeting the acceptable threshold of > 0.80 for complex models.

In conclusion, all fit indices satisfy the recommended criteria, demonstrating that the structural model possesses a high degree of compatibility with the empirical data. This validates the robustness of the model for subsequent hypothesis testing.

**Table 5.** Model fitting results

| Fit index | Recommended Threshold | Observed Value | Evaluation Result |
|---|---|---|---|
| CMIN/DF | <3 | 1.310 | Excellent |
| GFI | >0.8 | 0.899 | Excellent |
| CFI | >0.9 | 0.970 | Excellent |
| TLI | >0.9 | 0.967 | Excellent |
| RMSEA | <0.08 | 0.030 | Excellent |

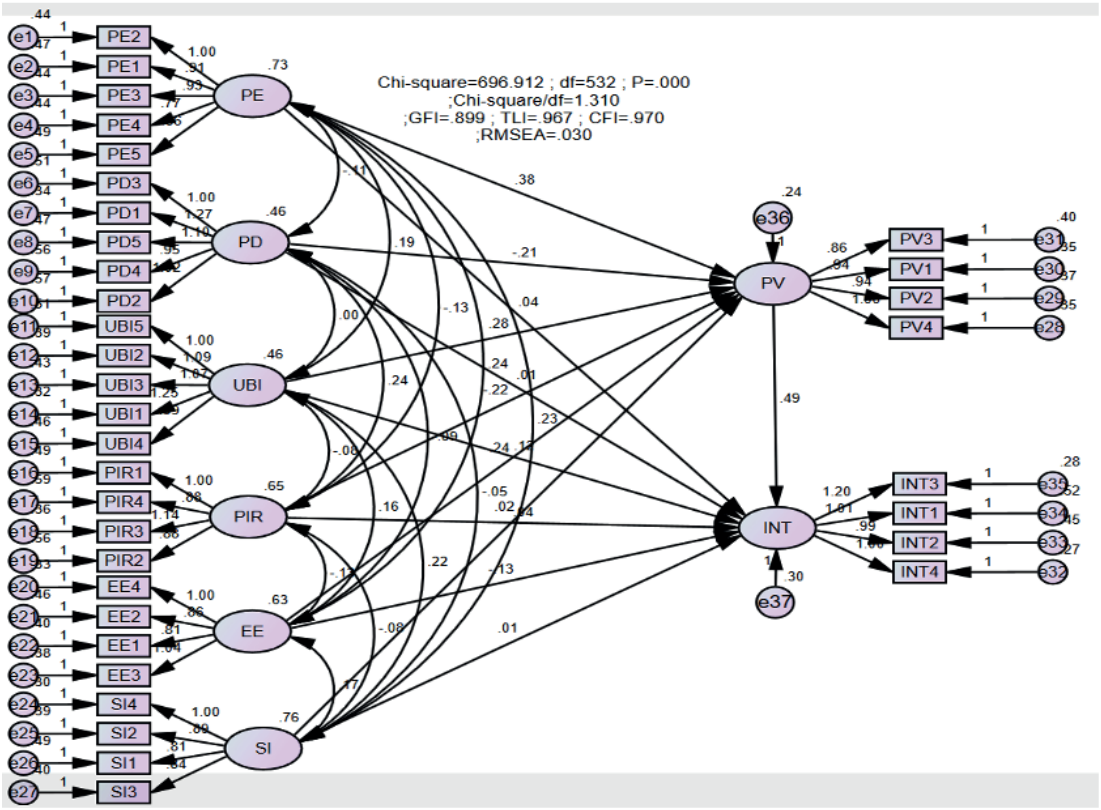


**Figure 1.** Research model values

## Path Analysis Results

The structural model was evaluated to determine the significance of the hypothesized relationships using the bootstrapping method (5,000 subsamples). The results, including standardized path coefficients (β), critical ratios (t-values), and significance levels (p-values), are summarized in Table 6.

*The Drivers of Perceived Value (Benefits):* Among the positive antecedents, PE emerged as the strongest predictor of PV (β = 0.399, t = 7.249, p < 0.001), providing strong support for H1. This indicates that utility and grade improvement are the primary value drivers for accounting students. UBI also demonstrated a substantial positive impact (β = 0.244, t = 4.559, p < 0.001), supporting H4, followed closely by EE (β = 0.219, t = 4.310, p < 0.001), which supported H2.

However, SI failed to predict PV significantly (β = 0.027, t = 0.545, p = 0.586). Consequently, H3 was rejected. This non-significant finding suggests that for students preparing for high-stakes individual certification exams, the decision to use mobile learning is driven by personal utility rather than peer or mentor pressure.

*The Barriers to Perceived Value (Sacrifices):* As hypothesized, both sacrifice factors negatively affected the students' valuation of the technology. PIR exerted a significant negative influence (β = -0.214, t = 4.083, p < 0.001), supporting H5. Similarly, PD was found to be a significant barrier (β = -0.173, t = 3.311, p < 0.001), supporting H6. These negative coefficients confirm that fear of inaccurate content and the cognitive cost of digital interruptions significantly diminish the perceived value of MML.

Finally, the relationship between PV and the INT was positive and highly significant (β = 0.584, t = 9.362, p < 0.001), supporting H7. The high critical ratio indicates that PV is the decisive determinant of adoption behavior in this context.

The explanatory power of the structural model was evaluated using the Coefficient of Determination ($R^2$), which indicates the proportion of variance in the endogenous constructs explained by their respective antecedents. According to the criteria established by Hair et al. (2010), $R^2$ values are categorized as substantial, moderate, or weak based on the specific research context. The results of the variance assessment are as follows:

The model achieved an $R^2$ value of 0.652, indicating that the combination of PE, EE, SI, UBI, PIR, and PD explains 65.2% of the variance in PV. This represents a moderate-to-strong explanatory power, suggesting that the integrated UTAUT-VAM framework captures the primary factors influencing how accounting students evaluate mobile micro-learning tools.

The model yielded an $R^2$ value of 0.372, signifying that PV explains 37.2% of the total variance in students' INT of MML.e While this is considered a moderate effect size in behavioral science, it underscores that PV is a significant predictor, though other external factors (such as institutional requirements or financial costs) may also contribute to the remaining variance.

**Table 6.** Results of Hypothesis Testing

| Hypothesis | Path | Std. Beta (β) | Critical Ratio | p-value | Result |
|---|---|---|---|---|---|
| H1 | PE a PV | 0.399 | 7.249 | 0.000 | Supported |
| H2 | EE a PV | 0.219 | 4.310 | 0.000 | Supported |
| H3 | SI a PV | 0.027 | 0.545 | 0.586 | Rejected |
| H4 | UBI a PV | 0.244 | 4.559 | 0.000 | Supported |
| H5 | PIRa PV | -0.214 | -4.083 | 0.000 | Supported |
| H6 | PD a PV | -0.173 | -3.311 | 0.000 | Supported |
| H7 | PV a INT | 0.584 | 9.362 | 0.000 | Supported |

## Hypothesis Testing Results – Indirect Effects

To examine the mediating role of PV (H8a–H8f), a bootstrapping analysis with 5,000 resamples was conducted to estimate the indirect effects and their corresponding 95% bias-corrected confidence intervals

(CI). The results, summarized in Table 7, confirm that PV acts as a critical mechanism translating technical antecedents into adoption intention.

It is important to note that the mediation analysis was conducted using a simultaneous estimation approach within the structural equation model. Consequently, when estimating the specific indirect path of a given antecedent (e.g., PE), the effects of all other exogenous variables (e.g., EE, SI, UBI, etc.) were statistically controlled for. This ensures that the reported mediation effects represent the unique contribution of each predictor while holding other factors constant.

Specifically, PE ($\beta = 0.233$, $p < 0.001$) and UBU ($\beta = 0.137$, $p < 0.001$) exerted robust positive indirect effects on the Intention to Adopt. The absence of significant direct effects for these variables (as reported in the total effects model) suggests a full mediation mechanism, supporting H8a and H8d. This indicates that utility and accessibility influence adoption behavior primarily by enhancing the user's valuation of the micro-learning tool.

Regarding EE (H8b), the analysis revealed a significant positive indirect effect ($\beta = 0.139$, $p < 0.05$). However, this must be interpreted in conjunction with the significant negative direct effect observed ($\beta = -0.150$). This pattern indicates a competitive partial mediation, suggesting that while ease of use contributes to PV, it simultaneously triggers a direct scrutiny regarding the rigor of the tool in a high-stakes learning context.

Conversely, the inhibitors - PIR ($\beta = -0.130$, $p < 0.05$) and PD ($\beta = -0.103$, $p < 0.05$) - demonstrated significant negative indirect effects. This supports H8e and H8f, confirming that these barriers reduce adoption intention by eroding the perceived net value of the learning experience.

Finally, the indirect effect of SI was not statistically significant ($\beta = 0.015$, $p > 0.05$), as the 95% confidence interval included zero. Thus, H8c was not supported, reinforcing the observation of "academic individualism" among the accounting students sampled.

**Table 7.** Results of Mediation analysis

| Hypothesis | Path | Total Effect (c) | Direct Effect (c') | Indirect Effect (a*b) | Mediation Type |
|---|---|---|---|---|---|
| H8a | PE a PV a INT | 0.230 | 0.053 (ns) | 0.233*** | Full mediation |
| H8b | EE a PV a INT | -0.010 | -0.150* | 0.139*** | Competitive Partial Mediation |
| H8c | SI a PV a INT | 0.023 | 0.014 (ns) | 0.015 (ns) | Rejected |
| H8d | UBI a PV a INT | 0.256 | 0.115 (ns) | 0.137*** | Full mediation |
| H8e | PIR a PV a INT | -0.073 | 0.043 (ns) | -0.130*** | Full mediation |
| H8f | PD a PV a INT | 0.093 | 0.011 (ns) | -0.103** | Full mediation |

*(Note: *** p<0.001; ** p<0.01; * p<0.05; ns: not significant. Total Effect = Direct + Indirect)*

## DISCUSSION

### The Primacy of Utilitarian Benefits

Consistent with the core tenets of VAM and prior studies (Kim et al., 2007; Venkatesh et al., 2003), PE emerged as the most significant positive driver of PV ($\beta = 0.399$). This finding aligns with the pragmatic nature of the Vietnamese accounting education context. In Vietnam, the accounting labor market is hyper-competitive, with a strong emphasis on professional certifications (e.g., CPA Vietnam, ACCA). Consequently, students exhibit a high degree of instrumental rationality; they value technology not for its novelty, but strictly for its utility in enhancing exam performance and employability.

Similarly, UBI was found to be a critical value driver. This resonates with the lifestyle of modern Vietnamese students, who often juggle academic requirements with part-time employment or internships. The ability to utilize fragmented time - such as commuting in traffic or breaks between shifts - transforms "dead time" into productive learning hours, thereby significantly enhancing the perceived worth of MML applications.

## The Shift in Social Influence

Contrary to the original hypotheses, SI did not significantly affect PV or INT. While this contradicts some general e-learning studies, it is theoretically consistent with the Voluntariness Moderator in the original UTAUT model (Venkatesh et al., 2003). Venkatesh posited that social norms strongly influence behavior only in mandatory settings (e.g., organizational implementation). In the voluntary context of self-directed exam preparation, the pressure to conform diminishes.

Furthermore, this finding aligns with the "Pragmatic Adoption" perspective in high-stakes education. As noted by Ngampornchai & Adams (2016), when learners face critical assessments, their decision-making becomes highly instrumental. The utilitarian value of the tool (Does it help me pass?) overshadows social approval (Do my peers use it?). Thus, in the fierce environment of accounting certification, functional utility acts as a dominant driver, rendering social pressure statistically insignificant.

This result contradicts traditional assumptions about Vietnamese culture, which is typically characterized as collectivist and highly susceptible to peer pressure (Hofstede, 2001). However, this deviation can be explained by the specific context of "Deep Learning" in accounting. Unlike social networking apps where critical mass is essential, exam preparation is an inherently solitary and competitive endeavor. This finding suggests a generational shift among Vietnamese Gen Z students towards academic individualism. They are increasingly selective, prioritizing personal efficacy over the "bandwagon effect." In the context of high-stakes testing, a student will not value an app simply because lecturers or peers recommend it; they must personally validate its effectiveness. This implies that for educational tools in Vietnam, "Word of Mouth" is less effective than "Proof of Utility."

## The Cognitive Cost: Distraction and Risk

The study validates the existence of significant barriers, with both PIR and PD negatively affecting PV. These findings must be interpreted through the dual lens of the Vietnamese cultural context and the specific demands of accounting education. First, Vietnam is characterized by High Uncertainty Avoidance (Hofstede, 2001). This cultural trait, reinforced by the meticulous nature of the accounting profession, explains the strong sensitivity to Information Risk and Perceived Distraction. For students preparing for high-stakes CPA exams, the tolerance for ambiguity or error is minimal, making trust and focus critical determinants of adoption.

The significance of PIR ($\beta = -0.187$) is particularly salient in the Vietnamese accounting context, where tax laws and financial regulations undergo frequent amendments. Students harbor a latent fear that mobile apps may contain outdated or unverified data, which could be detrimental in an exam setting. This mirrors the findings of Featherman and Pavlou (2003), suggesting that trust in content accuracy is a prerequisite for PV.

Furthermore, the negative impact of PD ($\beta = -0.169$) highlights the double-edged sword of mobile technology. While Vietnamese students are digital natives, they are acutely aware that the "always-on" nature of mobile devices - replete with social media notifications (Facebook, TikTok) - fragments the sustained attention required for complex accounting problems. This supports the Cognitive Load Theory (Sweller, 1988), confirming that when extraneous load (distraction) increases, the perceived utility of the learning tool decreases.

## The Paradox of Effort Expectancy

An intriguing finding emerged regarding the role of Effort Expectancy (EE), which demonstrated a competitive mediation mechanism: while EE positively influences Intention to Adopt (INT) via Perceived Value ($\beta = 0.139$), it exerts a significant negative direct effect on INT ($\beta = -0.150$, $p = 0.027$). To interpret this counter-intuitive result, this study proposes a crucial theoretical distinction between navigational ease (interface usability) and instructional ease (cognitive demand of the content). While a seamless interface (navigational ease) positively contributes to the tool's overall perceived value, an application that makes the learning process feel too effortless or over-gamified (instructional ease) triggers skepticism. This skepticism is particularly pronounced in the high-stakes context of accounting education - and further reinforced by

the Vietnamese "Confucian work ethic," which heavily values diligence and rigorous practice. Consequently, students often associate excessive "ease of use" with a lack of academic rigor, mirroring findings by Sun and Zhang (2006) and Hwang et al. (2012), who noted that experienced users tackling complex tasks perceive overly simplistic interfaces as functionally inadequate.

This behavioral paradox perfectly aligns with the framework of "desirable difficulties" (Bjork, 1994) . Accounting students, acting as rational investors of time, intuitively understand that mastering complex regulatory frameworks and preparing for rigorous CPA examinations require "productive struggle." Without the desirable cognitive difficulty necessary for long-term retention and complex problem-solving, an oversimplified tool is deemed inadequate for serious exam preparation. Therefore, Vietnamese accounting students prioritize tools that facilitate effective, deep learning (indirect effect via PV) over those that merely offer effortless interaction. Ultimately, this theoretical dynamic explains the empirical negative direct effect: an instructional experience lacking necessary cognitive friction directly diminishes the intention to adopt the tool as a primary, reliable study method.

### The Mediating Role of Perceived Value

Unlike traditional technology acceptance models (such as TAM or UTAUT), which often assume a direct path from technical attributes to INT, this study reveals that these attributes must first be converted into a perception of "Net Benefit." The mediation analysis indicates that PE, EE, and UBI do not trigger adoption in isolation. Instead, they serve as inputs for a mental calculus where students weigh these benefits against the "costs" of PIR and PD. This mirrors recent findings in the EdTech domain by Tian et al. (2024), who argued that in high-stakes educational environments, functional features are meaningless unless they translate into a tangible perception of worth.

The decisive role of PV in this study is particularly resonant with the Vietnamese context. Recent research on Vietnamese consumer behavior by Le et al. (2025) demonstrated that PV is a multidimensional construct that significantly outperforms satisfaction in predicting loyalty and behavioral intention. Our findings extend this logic from the consumer market to the educational sector. Vietnamese accounting students, facing the immense pressure of professional certification exams, exhibit a high degree of "instrumental rationality." They view their study time as a scarce resource and the mobile app as an investment.

When the "Net Value" is positive (i.e., the utility of learning anywhere outweighs the annoyance of notifications), they form an intention to adopt. This explains why PD has such a potent indirect negative effect on intention. It is not merely a nuisance; in the eyes of a pragmatic Vietnamese student, distraction represents a "devaluation" of the learning asset.

Furthermore, the mediation analysis highlights that the barriers to adoption – PIR and PD - operate exclusively through PV. This suggests that students do not reject MML simply because it is risky or distracting per se; they reject it when these sacrifices erode the overall value proposition to a point where the "trade-off" is no longer profitable. This nuanced understanding validates the superiority of the VAM framework over UTAUT in explaining the complex, ambivalent relationship students have with their mobile devices - seeing them simultaneously as essential tools and potential hindrance.

## CONCLUSION

### Summary of the Study

As the accounting profession demands increasingly rigorous certification standards (e.g., CPA, ACCA), the pedagogical landscape must evolve to accommodate the time-constrained lifestyles of modern students. This study addressed the critical need to understand the determinants of MML adoption by moving beyond traditional technology acceptance models. By integrating the TAUT with the VAM, this research elucidated MML adoption not merely as a technological imperative but as a cognitive trade-off between functional benefits and distinct sacrifices.

The empirical analysis of 342 Vietnamese accounting students reveals that the decision to adopt MML is driven primarily by instrumental utility. Students act as rational value maximizers; they embrace mobile

learning when it offers Ubiquity (flexibility) and Performance Expectancy (exam success). However, this utility is significantly compromised by the "dark side" of mobile connectivity - specifically Perceived Distraction and Information Risk

## Theoretical Implications

This study offers three significant contributions to the EdTech and Accounting Education literature:

1. *Validation of VAM in High-Stakes Education:* Unlike previous studies that overwhelmingly focus on positive drivers, this research confirms that "sacrifices" are equally potent. By quantifying the negative impact of Perceived Distraction, the study challenges the uncritical promotion of mobile learning, suggesting that for cognitively demanding tasks like accounting, the device itself acts as a structural barrier to deep work.
2. *The "Solitary Learner" Phenomenon*: The rejection of the Social Influence hypothesis provides a nuanced cultural insight. It suggests that in the context of high-stakes professional exams, Vietnamese Gen Z students exhibit "academic individualism." They are immune to peer pressure regarding study tools, prioritizing personal verification of utility over collective endorsement. This finding prompts a re-evaluation of collectivist assumptions in modern educational technology research.
3. *The Centrality of Perceived Value:* The results firmly establish Perceived Value as the indispensable mediator. Technical features alone (e.g., ease of use) are insufficient to trigger adoption unless they translate into a tangible net benefit, validating the applicability of rational choice theory in student behavior.
4. *Moving Beyond Replication*: The Role of Rigor over Ease While previous studies have replicated UTAUT across various contexts, this research advances existing knowledge by identifying a critical boundary condition for the "Ease of Use" construct. By revealing the competitive partial mediation of EE (where the direct effect is negative), this study challenges the universal applicability of "ease" as a driver. This research proposes that in high-stakes, competency-based disciplines, the technology adoption meta-framework must account for "Instrumental Rigor" - where users may prioritize tools that support deep, effortful learning over those that offer superficial ease.

## Practical Implications

The findings provide actionable intelligence for stakeholders in the EdTech ecosystem:

1. *For App Developers (Mitigating Distraction*): Recognizing that distraction is a primary value-destroyer, developers should engineer "Focus Modes" into accounting apps. Features such as locking the screen during quizzes, muting external notifications, or gamifying "focus streaks" could directly alleviate the cognitive load identified in this study.
2. *For Content Providers (Mitigating Risk):* To counter Perceived Information Risk, content must be visibly authenticated. Integrating "Verified by CPA" badges, citing specific regulatory clauses (e.g., *VAS/IFRS Standards 2025*), and displaying "Last Updated" timestamps are crucial for building trust.
3. *For Educators (Focus on Utility, Not Trends):* Given that Social Influence is non-significant, educators should stop relying on "recommendations" to drive adoption. Instead, they must demonstrate the Performance Expectancy of these tools - showing explicitly how specific app modules correlate with higher pass rates in certification exams.

## Limitations and Future Research

While this study provides robust insights, it is not without limitations. First, the cross-sectional design captures intention at a single point in time; it does not track whether this intention translates into long-term sustained usage. Future research should employ longitudinal designs to measure actual usage behavior over an entire semester. Second, the sample was restricted to accounting students in Vietnam. While this provides specific cultural insights, it limits generalizability. Comparative studies across different ASEAN nations could

determine if the irrelevance of Social Influence is a unique Vietnamese phenomenon or a regional trend. Third, the study employed a cross-sectional design with a convenience sample of accounting students. While this approach effectively captures the specific perceptions of this target group at a single point in time, it limits the ability to draw causal inferences or observe behavioral changes over time. Future research should employ longitudinal designs to validate whether these initial intentions translate into sustained long-term usage. Finally, future scholars could investigate the moderating role of "Self-Regulation," exploring whether students with higher self-discipline can better mitigate the negative effects of perceived distraction.

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