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What drives teachers' intention to integrate digital technologies? Positioning value beliefs about technology within the Technology Acceptance Model

Che cosa determina l'intenzione degli insegnanti di integrare le tecnologie digitali nella didattica? Il ruolo e il posizionamento delle credenze sul valore della tecnologia nel Modello di Accettazione della Tecnologia

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Abstract
International agendas have long urged education systems to embed digital competence, yet technology integration remains uneven. The Technology Acceptance Model (TAM) explains teachers' behavioural intention (BI) and technology use through perceived usefulness (PU), perceived ease of use (PEU), and attitudes (ATT). However, the role and placement of teachers' value beliefs about technology (VALUE) remain unclear. This study integrates VALUE into a TAM-anchored network and tests its functional role. An online cross-sectional survey was completed by Italian pre-service and in-service teachers (N = 375). PU, PEU, and ATT were measured with a semantic differential scale; BI with three items; and VALUE with a six-item scale. Analyses comprised hierarchical regression and path analysis, comparing specifications by BIC/AIC and global fit. Adding VALUE to the TAM baseline yielded a significant increment in explaining BI (ΔR^2 = .084; f^2 = .176). In path models, specifications including a direct VALUE→BI path consistently dominated information-equivalent alternatives. The best-fitting model treated VALUE as endogenous to PU and ATT and retained VALUE→BI (CFI = .994, TLI = .969, RMSEA = .085, SRMR = .021; R^2(BI) = .515). In this model, the VALUE→BI path was large (β = .386), while direct PU→BI and ATT→BI were attenuated, consistent with VALUE capturing proximal variance in BI. No empirical justification emerged to add a PEU-VALUE linkage. Findings clarify that VALUE is a distinct construct, positioned downstream of PU/ATT and exerting a unique direct influence on BI. Results have implications for refining TAM and for designing teacher education and professional development.

Keywords: Technology integration; Technology Acceptance Model (TAM); Value beliefs about technology; Teachers.

Riassunto
Da tempo i sistemi educativi sono sollecitati a integrare la competenza digitale, tuttavia l'integrazione della tecnologia resta disomogenea. Il Technology Acceptance Model (TAM) spiega l'intenzione comportamentale (BI) degli insegnanti e l'uso della tecnologia attraverso l'utilità percepita (PU), la facilità d'uso percepita (PEU) e gli atteggiamenti (ATT); resta però poco chiaro il ruolo delle credenze di valore sulla tecnologia (VALUE). Questo studio integra VALUE nel TAM e ne esamina ruolo e posizionamento tramite un'indagine online che ha coinvolto 375 insegnanti italiani in formazione iniziale e in servizio. PU, PEU e ATT sono stati rilevati con una scala a differenziale semantico, BI con tre item e VALUE con una scala a sei item. Le analisi hanno incluso regressione gerarchica e path analysis, con confronto dei modelli tramite BIC/AIC e indici di adattamento globale. L'aggiunta di VALUE al TAM incrementa la varianza spiegata di BI (ΔR^2 = .084; f^2 = .176). Il modello con il miglior adattamento posiziona VALUE come endogeno a PU e ATT e mantiene VALUE→BI (CFI = .994, TLI = .969, RMSEA = .085, SRMR = .021; R^2(BI) = .515). In questo modello, VALUE→BI è ampio (β = .386), mentre PU→BI e ATT→BI risultano attenuati, coerentemente con un ruolo prossimale di VALUE su BI; non emerge evidenza per un legame PEU-VALUE. I risultati indicano che VALUE costituisce un costrutto distinto, a valle di PU/ATT, con un effetto unico e diretto su BI. Ne derivano implicazioni per il perfezionamento del TAM e per la progettazione della formazione docente.

Parole chiave: Integrazione della tecnologia; Modello di Accettazione della Tecnologia (TAM); Credenze di valore sulla tecnologia; Insegnanti.

1. Introduction

International policy agendas have, for more than two decades, urged education systems to embed digital competence within curricula and teacher professional standards, and to prepare students as digitally literate citizens able to navigate contemporary societies (e.g., European Commission, 2001, 2018, 2020a, 2020b; European Council, 2014, 2017, 2018; European Parliament and Council, 2006; OECD, 2023). Despite these imperatives, technology integration remains uneven and frequently suboptimal, reflecting the complexity of transforming pedagogical practice and the variability of contextual conditions across schools and systems (e.g., European Commission, 2019; OECD, 2019). Explanations for successful versus hindered technology integration commonly distinguish between first-order (external) barriers – such as infrastructure, access to devices and software, time, and institutional support – and second-order (internal) barriers, notably teachers' beliefs and attitudes regarding technology and learning (Ertmer et al., 2015; Hew & Brush, 2007). Whereas first-order barriers can often be identified and addressed at the organisational level, second-order barriers require shifts in how teachers conceive of teaching, learning and the role of technology.

Within this landscape, technology-acceptance frameworks have provided influential accounts of the determinants of teachers' behavioural intention and use of educational technologies. The Technology Acceptance Model (TAM) has been especially prominent because of its parsimony, transferability across contexts and amenability to structural modelling (Marangunić & Granić, 2015). Core TAM constructs – perceived usefulness (PU), perceived ease of use (PEU), and attitudes towards technology (ATT) – are theorised and proven to shape behavioural intention (BI) and subsequent use (USE). Syntheses specific to teacher populations (e.g., Scherer & Teo, 2019; Scherer et al., 2015; Scherer et al., 2019) corroborate key pathways: PU exerts both an indirect effect on BI via ATT and an additional direct effect on BI, whereas PEU influences BI primarily indirectly via ATT; ATT is a significant predictor of BI and, beyond its indirect pathway through BI, also shows a direct association with USE.

Moreover, teachers' value beliefs about technology – beliefs that technology is an important and beneficial tool for teaching and learning – have emerged as critical determinants of technology integration. Studies indicate that when teachers ascribe higher value to technology, they use it more frequently and in more sophisticated, student-centred ways, translating mere access into purposeful classroom applications (e.g., Hsu, 2016; Taimalu & Luik, 2019). Where technology is valued, teachers more readily mobilise resources and persist in the face of infrastructural or time constraints, investing the effort required for meaningful use (Vongkulluksn et al., 2018). Taken together, this literature indicates that value beliefs constitute a proximal driver of behavioural intention and classroom use.

In this context, the present study integrates value beliefs about technology into the TAM network and assesses their functional role through comparative model testing. It is hypothesised that value beliefs complement – and may add explanatory power beyond – PU, PEU, and ATT. Accordingly, this study examines whether value beliefs contribute uniquely and directly to teachers' intention to use digital technologies for teaching within a TAM-anchored framework. Clarifying whether, how and where value beliefs operate is expected to refine theory – by delineating the distinctiveness and placement of VALUE relative to PU, PEU, and ATT – and to inform teacher education and professional development by indicating whether efforts should target teachers' value beliefs directly, prioritise shifts in PU, PEU, and ATT, or a combination of these.

2. Theoretical background

2.1 Technology Acceptance Model

The TAM was first proposed by Davis (1985) and developed from the Theory of Reasoned Action (TRA; Ajzen & Fishbein, 1980; Davis et al., 1989; Fishbein & Ajzen, 1975). The model comprises core variables that directly or indirectly explain the outcome variables, along with external variables representing personal capabilities and contextual factors (Schepers & Wetzels, 2007). Specifically, the core variables are PU, PEU, and ATT; the outcome variables are BI and actual technology USE (Marangunić & Granić, 2015).

Among the most frequently examined external variables are subjective norms, self-efficacy, and facilitating conditions, which are significantly associated with the core variables, albeit to different degrees (e.g., Abdullah & Ward, 2016; Baydas & Goktas, 2017; Schepers & Wetzels, 2007).

2.1.1 Key concepts in TAM

Within TAM, PU and PEU denote the extent to which an individual believes that using a technology would enhance job performance (PU) and be free of effort (PEU) (Davis, 1989). These perceptions link directly to another central construct: ATT, understood as a person's evaluation of the technology or of the specific behaviour associated with its use (Zhang et al., 2008). TAM then considers BI and USE as outcome variables. Drawing on TRA, BI captures planned behaviour – i.e., a person's intention to use the technology – whereas USE refers to observable behaviour – i.e., the actual use of the technology (Scherer et al., 2019). Finally, TAM's external variables include subjective norms (SN), (computer) self-efficacy (CSE), and facilitating conditions (FC). SN concerns an individual's perception that significant others think they should – or should not – perform the behaviour in question, i.e., perceptions of how important referents value technology use (Fishbein & Ajzen, 1975; Taylor & Todd, 1995). CSE refers to the extent to which a person believes they can accomplish specific tasks using technology, i.e., perceptions of one's ability to master computer- or technology-related tasks and to use digital devices effectively (Compeau & Higgins, 1995; Taylor & Todd, 1995). FC denotes the degree to which a person believes that organisational and technical resources exist to support technology use, i.e., perceptions of organisational support in terms of resources, structures, and assistance (Venkatesh et al., 2003; Taylor & Todd, 1995).

2.1.2 Relationships within TAM

A substantial body of studies, reviews, and meta-analyses has examined the interrelations among TAM variables in teaching and learning contexts, to shed light on the mechanisms underpinning pre-service and in-service teachers' technology acceptance and adoption and to distil implications relevant to teacher education and professional development. A recent meta-analysis by Scherer and colleagues (2019) synthesised existing findings on teachers' (pre- and in-service) technology acceptance and specified the model and relationships depicted in Fig. 1. Below, only the relationships considered in this contribution are described; for the role and effects of other variables, see Scherer et al. (2019).

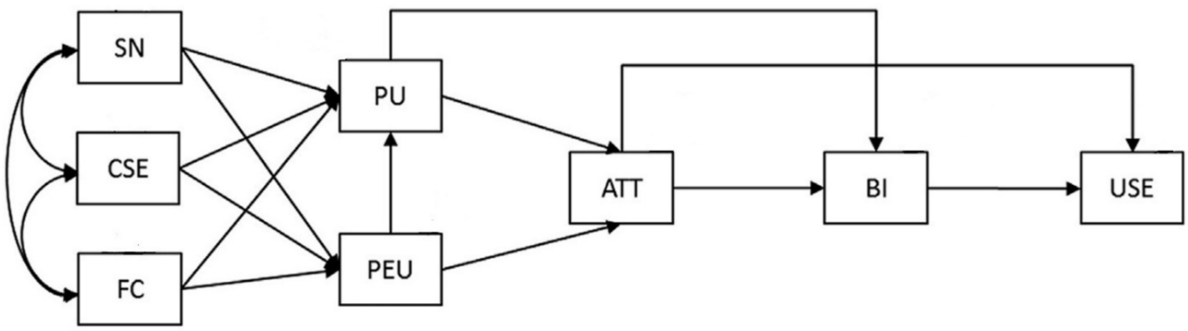

Fig. 1: Technology Acceptance Model[1]

The role of perceived usefulness and perceived ease of use. Regarding PU and PEU, the meta-analysis showed that PU, alongside PEU, significantly predicts BI via ATT towards technology, with ATT functioning as a mediator. This finding underscores the importance of teachers' perceptions and attitudes for their intentions: the higher the PU and PEU, the greater the intention to employ technology; conversely, lower perceptions are associated with greater difficulty in accepting and adopting technologies. Moreover, effects on BI are markedly stronger for PU than for PEU. In addition to the indirect pathway, a direct

1 Adapted from Scherer et al., 2019 (p. 16).

effect from PU to BI was also observed. PU thus appears to be a critical determinant of teachers' intentions.

The role of attitudes. ATT is a significant predictor of BI, and beyond its indirect effect on USE via BI, a direct effect of ATT on USE has also been identified. This further attests to the salience of attitudes for actual use behaviour. Numerous studies have repeatedly shown a strong association between attitudes towards technologies and their use in educational settings (e.g., Nistor & Heymann, 2010; Scherer et al., 2018; van Braak, 2001) and that a positive attitude towards technology plays a crucial role in its effective integration (Voogt et al., 2011).

2.2 Teacher beliefs about technology

Research on teacher beliefs is extensive yet lacks a shared definition: frameworks differ in how beliefs are conceptualised, operationalised, and measured (Kim et al., 2013; Pajares, 1992). This lack of consensus extends to teachers' beliefs about technology. Some studies equate them with beliefs about the value of technology for student learning (e.g., Polly et al., 2010); others with technology-use self-efficacy (e.g., Abbitt, 2011); still others treat them as a composite of self-efficacy, value beliefs about technology, and beliefs about teaching and learning with technology (e.g., Park & Ertmer, 2007). In this paper, beliefs are conceived as a personal system of more or less structured opinions, generalisations, expectations, values, and rules of thumb (Hermans et al., 2008). Within this system, beliefs about technology are taken to be personal views regarding the importance of technology for teaching, its potential positive or negative impact on student learning, and the benefits it may offer to teaching-learning processes (Russell et al., 2003).

Consistent evidence shows that teachers' beliefs are among the strongest determinants of technology integration and frequently the primary predictors of classroom technology use (Ertmer et al., 2012; Ertmer & Ottenbreit-Leftwich, 2010; Ottenbreit-Leftwich et al., 2010). When knowledge and skills are comparable, teachers' beliefs act as the decisive factor in whether or not they adopt technology (Kim et al., 2013). Within this landscape, two belief domains are especially salient for technology integration: pedagogical beliefs – teachers' conceptions of the nature of teaching and learning (Ertmer et al., 2015) – and value beliefs about technology. The latter are the focus of the present paper; the remainder of this section, therefore, examines teachers' value beliefs about technology and their specific implications for integration.

2.2.1Value beliefs about technology

Research on teachers' technology-related beliefs underscores the pivotal role of the *value* attributed to technologies for teaching and for students' learning (Ottenbreit-Leftwich et al., 2010; Park & Ertmer, 2007). When teachers perceive technology as valuable in teaching and learning, they tend to integrate it more frequently into their pedagogical practice (Hsu, 2016; Ottenbreit-Leftwich et al., 2010; Taimalu & Luik, 2019). In other words, beliefs about the value of technologies strengthen perceptions of their effectiveness for teaching and learning, which, in turn, shape subsequent use (Ottenbreit-Leftwich et al., 2010; Park & Ertmer, 2007).

Moreover, teachers who hold more facilitative value beliefs (e.g., believing that technology is important for instruction and beneficial for sustaining student learning) are more likely to mobilise resources to surmount external barriers – such as limited internet access, constrained availability of/access to hardware/software, insufficient time for professional development or planning, and restricted administrative support – when integrating technology (Snoeyink & Ertmer, 2001; Vongkulluksn et al., 2018). Given the substantial preparation required – i.e., the investment of energy, resources, and time – for meaningful technology integration, these value beliefs become especially salient; where technology is not valued, investment is unlikely (Coppola, 2004; Zhao & Cziko, 2001). Consequently, it is reasonable to posit that teachers must first ascribe value to technology use before integrating it into their practice (Zhao & Cziko, 2001), and they must believe that technology use will contribute to sound teaching and desired learning outcomes (Taimalu & Luik, 2019).

Evidence indicates that teachers' beliefs about the value of technology are strong predictors of both the quantity and quality of technology integration; in particular, higher value beliefs are associated with more student-centred uses and the orchestration of higher-order learning tasks (Vongkulluksn et al., 2018). In sum, beliefs, and especially value beliefs, are closely bound up with technology use in education (Ertmer & Ottenbreit-Leftwich, 2010; Ottenbreit-Leftwich et al., 2010).

3. The present study

3.1 Procedure and participants

A cross-sectional survey was conducted online with a convenience sample of pre-service and in-service teachers. Data were collected via an online questionnaire distributed to teachers preparing for secondary school teaching through *percorsi abilitanti di formazione iniziale* (pre-service teachers) and to participants in continuous professional development and training activities (in-service teachers). Participation was voluntary and anonymous; informed consent was obtained electronically prior to survey access.

The sample comprised 375 participants. Their ages ranged from 24 to 60 years (M = 37.8, SD = 9.57, Median = 36). Most participants identified as female (n = 247, 65.9%), followed by male (n = 122, 32.5%), with 6 respondents (1.6%) selecting "prefer not to say". The sample included 158 pre-service teachers (42.1%) and 217 in-service teachers (57.9%). Specifically, 17.3% (n = 65) reported teaching in lower secondary school and 40.5% (n = 152) in upper secondary school.

3.2 Instruments

To measure TAM constructs, the study used the TECNOINS scale (*Teachers' Perceptions and Attitudes towards the Use of Digital Technologies in Teaching*), a 5-point semantic differential instrument comprising ten pairs of opposite adjectives, arranged into three TAM-aligned subscales: ATT (4 pairs), PEU (3), and PU (3). Prior validation with Italian teachers supports a three-factor solution and acceptable-to-good internal consistency (Foschi, 2022).

To assess BI, three items were developed for this study, aligned with TAM practice, to assess intention to use digital technologies in teaching (agreement, strength, and likelihood; 5-point Likert-type response scales). The BI score was computed as the mean of the three items[2].

To capture value beliefs about technology (VALUE), the study used the TECNOVAL scale (*Beliefs about the Value of Digital Technology in Teaching*), a 6-item, 5-point Likert-type instrument (1 = strongly disagree to 5 = strongly agree) representing a single latent factor ("Technology as a valuable instructional tool"), with factor loadings ranging from .49 to .79, and reliability estimates adequate for research use in prior work (Foschi, 2024).

3.3 Research questions

The study examined pre- and in-service teachers' perceptions and attitudes towards the use of digital technologies in teaching (PU, PEU, ATT), value beliefs about technology (VALUE), and behavioural intention to use digital technologies in teaching (BI).

The study addressed the following research questions (RQs):

2 The psychometric properties of this three-item scale in the present sample are the following. The correlation matrix was found to be factorable (pseudo χ^2 = 447, df = 3, p < .001; KMO = .69). The subsequent exploratory factor analysis (EFA), conducted with principal-axis factoring extraction and oblique oblimin rotation, yielded a one-factor solution (parallel analysis, scree-test, and Kaiser-Guttman criterion) consistent with the expectations. The factor was saliently loaded by all three variables, with factor loadings ranging from .64 to .89, and it explained 62.6% of the variance in the correlation matrix. The factor also demonstrated good internal consistency reliability (McDonald's ω = .83, Cronbach's α = .80).

- RQ1 – Incremental contribution. Does VALUE add unique predictive information to BI beyond PU, ATT, and PEU?
- RQ2 – Functional form of the contribution. Is VALUE's contribution to BI direct (i.e., via a VALUE→BI path) or predominantly indirect via PU and/or ATT (with PEU feeding into them as in TAM)?
- RQ3 – Position of VALUE within the TAM network. Should VALUE be modelled as exogenous (upstream) to the TAM core variables (PEU, PU, ATT) or modelled as endogenous (downstream)?
- RQ4 – Best-fitting specification. Which specification, among the candidate VALUE path models identified in RQ3, best balances fit and parsimony and best explains BI?

Analyses were sequenced such that RQ2 was undertaken conditional on evidence for incremental contribution in RQ1; RQ3 compared exogenous versus endogenous placements conditional on the RQ2 specification; and RQ4 compared the resulting candidate VALUE specifications and selected the best-fitting model.

3.4 Data analysis

Descriptives and reliability. For each multi-item scale, descriptive statistics (N, mean, median, standard deviation, skewness, kurtosis) were computed. All analyses used observed mean-composite scale scores (item means for each variable). Internal consistency was evaluated using Cronbach's α and McDonald's ω.

RQ1. Evidence for incremental contribution of VALUE to BI was assessed using hierarchical linear regression, with the TAM baseline predictors (PU, ATT, PEU) entered first and VALUE added in a second step. The increment was evaluated using ΔR^2 and F-change, along with associated df and p-value. For completeness, AIC and BIC were also computed for the two models, and the magnitude of the increment was summarised by Cohen's $f^2 = R^2/(1-R^2_{full})$ and the semi-partial correlation ($r_{sp} = \sqrt{(\Delta R^2)}$).

RQ2-RQ4[3]. To test the structure of VALUE's contribution and its placement within the TAM network[4], path analysis was conducted with Maximum Likelihood (ML) estimation. All path models were anchored on the TAM baseline and differed only in the additional VALUE relations specified for each research question:

- RQ2 (direct vs predominantly indirect): five pairs of nested models identical except for the inclusion/exclusion of VALUE→BI.
- RQ3 (position of VALUE): seven exogenous-VALUE specifications (VALUE modelled as upstream of PEU/PU/ATT) were contrasted with their direction-reversed endogenous counterparts (VALUE predicted by PEU/PU/ATT); VALUE→BI was retained in all models.
- RQ4 (best-fitting specification): the VALUE-endogenous candidates (Models 8-14) were compared, and – given the inconclusive role of PEU in RQ3 – an additional specification (Model 15) was estimated to adjudicate PEU's placement (VALUE→PEU) against the two leading alternatives (no PEU-VALUE link; PEU→VALUE).

Model comparison and selection. Competing models were compared using the Bayesian Information Criterion (BIC) and Akaike's Information Criterion (AIC) – lower indicated a better trade-off between fit and parsimony. BIC served as the primary selection metric, with conventional thresholds for BIC used to grade the evidence (0-2: weak evidence; 2-6: positive; 6-10: strong; >10: very strong) (Lorah & Womack, 2019). Where models were near equivalent by BIC, ties were resolved by parsimony and theoretical co-

3 Because RQ1 provided positive evidence for VALUE's incremental contribution and RQ2 supported a direct VALUE→BI path, RQ3 contrasted exogenous versus endogenous placements while retaining VALUE→BI; evidence for endogeneity then motivated RQ4, which compared VALUE-endogenous models to identify the preferred specification.

4 All path models were anchored on a teacher-focused TAM baseline derived from prior evidence (e.g., Scherer et al., 2019) and corroborated by the present data, consisting of the following paths: PEU→PU, PU→ATT, PEU→ATT, ATT→BI, PU→BI.

herence, and secondarily by AIC. Final retention decisions for RQ4 considered the union of evidence: information criteria, global fit, R^2(BI), and the pattern of direct/indirect effects.

Model-fit evaluation. Global fit was summarised by χ^2 (df, p), CFI, TLI, RMSEA (with 90% CI and PCLOSE), and SRMR. Interpretation followed widely cited guidelines (e.g., higher CFI/TLI, lower SRMR/RMSEA indicate better fit; particularly CFI/TLI ≥ .95, RMSEA ≤ .06, SRMR ≤ .08; Hu & Bentler, 1999), with explicit caveats: RMSEA is known to be upward-biased and prone to over-rejection in very small-df models (Kenny et al., 2015) – as here, df = 1-3, and the χ^2 test is highly sensitive to sample size, often rejecting acceptable models under large N (Browne & Cudeck, 1993). Accordingly, emphasis was placed on CFI/TLI and SRMR, and on RMSEA's 90% CI and PCLOSE, rather than on any single cut-off; χ^2 was not used as the sole arbiter of fit.

Estimates and effects. For each model, the following were obtained: standardised direct effects (β) with ML p-values and 95% bootstrap confidence intervals (percentile method, B = 5000), standardised indirect effects (β), and explained variance (R^2) for all endogenous variables.

4. Results

4.1 Descriptives and reliability

All variables used 5-point scales. Descriptive statistics (Tab. 1) showed high PU (M = 4.10, SD = .72), positive ATT (M = 4.14, SD = .71), and intermediate PEU (M = 3.10, SD = .88); BI was relatively high (M = 3.91, SD = .60). Scores on VALUE were positive (M = 3.92, SD = .60), i.e. technology is recognised as having high educational value. Each scale demonstrated reliability estimates (Tab. 1) in the acceptable-to-good range of internal consistency (George & Mallery, 2003).

	N	Mean	Median	SD	Skewness	Kurtosis	Cronbach's α	McDonald's ω
PEU	375	3.10	3	.882	.209	-.329	.79	.80
PU	375	4.10	4	.720	-.746	.908	.87	.87
ATT	375	4.14	4.25	.710	-.670	-.052	.84	.85
BI	375	3.91	4	.599	-.632	.454	.80	.83
VALUE	375	3.92	4	.600	-.527	1.074	.76	.80

Tab. 1: Descriptives and reliability

4.2 TAM baseline

The TAM baseline path model (PEU→PU; PU→ATT; PEU→ATT; ATT→BI; PU→BI) was estimated using Maximum Likelihood. Overall model fit was good, with a non-significant chi-square ($\chi^2(1) = 2.94$, p = .087); CFI = .997, TLI = .98; RMSEA = .072 (90% CI [.000, .174], PCLOSE = .231); SRMR = .020.The standardised structural paths were: PEU→PU β = .199 [.094, .299], p < .001[5]; PU→ATT β = .750 [.686, .803], p < .001; PEU→ATT β = .137 [.072, .205], p. < .001; ATT→BI β = .368 [.231, .525], p < .001; PU→BI β = .331 [.140, .498], p < .001. Standardised indirect effects were: PU→ATT→BI = .276; PEU→ATT→BI = .050; PEU→PU→BI = .066; PEU→PU→ATT→BI = .055. The model explained R^2 = .039 for PU, .622 for ATT, and .434 for BI.

5 Standardised coefficients (β) are reported with *p*-values from ML estimation; 95% bootstrap confidence intervals (percentile method, B = 5000) are shown in brackets.

4.3 RQ1

Whether VALUE adds unique predictive information to BI beyond PU, ATT, and PEU was tested using hierarchical linear regression.

Adding VALUE to the TAM baseline (PEU, PU, ATT) improved fit and predictive accuracy: explained variance in BI (R^2) rose from .438 (Adj. .434) to .522 (Adj. .517), yielding $\Delta R^2 = .084$, F-change(1, 370) = 65, $p < .001$. Information criteria decreased substantially (AIC 473→414, ΔAIC = -59; BIC 493→438, BIC = -55), and RMSE declined (.449→.414). The corresponding effect size for the increment is Cohen's $f^2 = .176$ (medium; Cohen, 1988), with semi-partial r = .29.

VALUE showed a strong unique association with BI (b = .393, SE = 0.049, t = 8.06, $p < .001$, 95% CI [0.297, 0.489], β = .394). The other predictors remained positive and significant: ATT (b = .183, SE = .051, t = 3.58, $p < .001$, β = .217), PU (b = .146, SE = .050, t = 2.90, p = .004, β = .175), and PEU (b = .061, SE = .026, t = 2.39, p = .017, β = .090). Type-III tests were all significant in the extended model (PEU: F = 5.71, p = .017; PU: F = 8.41, p = .004; ATT: F = 12.79, $p < .001$; VALUE: F = 65.03, $p < .001$).

Relative to a TAM baseline with PU, ATT, and PEU, adding VALUE yields a statistically robust and practically meaningful improvement in explaining BI ($\Delta R^2 = .084$; large F-change; ΔAIC/ΔBIC strongly negative). This establishes that VALUE contributes uniquely to BI and justifies proceeding to path analyses to determine whether that contribution is direct or predominantly indirect via PEU/PU/ATT.

4.4 RQ2

To test whether VALUE contributes to BI direct (i.e., via a VALUE→BI path) or predominantly indirect via PU and/or ATT (with PEU feeding into them as in TAM), five pairs of nested path models were compared. In all cases, models were anchored on the TAM baseline – specified as PEU→PU, PU→ATT, PEU→ATT, ATT→BI, PU→BI – and identical except for the presence or absence of a direct VALUE→BI path. Model selection relied on AIC and BIC (lower values indicate a better fit-parsimony trade-off). The five comparisons were 2 vs 20, 5 vs 19, 3 vs 21, 4 vs 18, and 7 vs 22 (see Tab. 8 in the Appendix).

Across all five nested comparisons, the models including a direct path from VALUE→BI had substantially lower BIC and AIC than the otherwise identical models without that path: 2 vs 20, BIC = 109.449 vs 161.287 and AIC = 58.399 vs 114.164; 5 vs 19, BIC = 88.701 vs 140.539 and AIC = 33.724 vs 89.489; 3 vs 21, BIC = 109.449 vs 161.287 and AIC = 58.399 vs 114.164; 4 vs 18, BIC = 280.382 vs 332.220 and AIC = 229.332 vs 285.097; 7 vs 22, BIC = 88.701 vs 140.539 and AIC = 33.724 vs 89.489.

Across all comparisons, the direct-path model dominated (ΔBIC = 51.838, ΔAIC = 55.765 in each pair), far exceeding conventional thresholds ($\Delta > 10$) for decisive evidence supporting the model with the lower criterion; thus, these results consistently indicate that VALUE contributes uniquely and directly to BI over and above pathways via PU, ATT, and PEU.

4.5 RQ3

To address RQ3 – whether VALUE should be modelled as exogenous (upstream) to the TAM core variables (PEU, PU, ATT) or modelled as endogenous (downstream), i.e., predicted by them –, seven exogenous-VALUE specifications (Models 1-7) were compared with their direction-reversed endogenous counterparts (Models 8-14) using AIC and BIC (lower values indicate a better fit-parsimony trade-off). In all specifications, models were anchored on the TAM baseline and retained the direct path VALUE→BI – consistent with the answer to RQ2. The results were as follows:

– PEU only (1 vs 8). The models were indistinguishable: BIC1 = BIC8 = 301.130; AIC1 = AIC8 = 254.007. Thus, with only PEU included alongside VALUE→BI, the data do not discriminate whether VALUE precedes or follows PEU. On information-theoretic grounds, the two structures are observationally equivalent in terms of fit.

– PU only (2 vs 9). The endogenous specification (PU→VALUE) was preferred: BIC9 = 103.553 < 109.449 (ΔBIC = 5.896) and AIC9 = 56.430 < 58.399 (ΔAIC = 1.969). By BIC, this positive (borderline "strong") support for treating VALUE as endogenous to PU; by AIC, the advantage is modest.
– ATT only (4 vs 11). The endogenous model (ATT→VALUE) was decisively preferred: BIC11 = 121.467 < 280.382 (ΔBIC = 158.915) and AIC11 = 74.344 < 229.332 (ΔAIC = 154.988).
– PEU + PU (3 vs 10). The models were again indistinguishable: BIC3 = BIC10 = 109.449; AIC3 = AIC10 = 58.399. With both PEU and PU included, treating VALUE as exogenous (upstream) versus endogenous (predicted by PEU/PU) yields information-equivalent fit.
– PEU + ATT (6 vs 13). The endogenous model (PEU→VALUE, ATT→VALUE) was decisively preferred: BIC13 = 125.212 < 280.382 (ΔBIC = 155.170) and AIC13 = 74.162 < 229.332 (ΔAIC = 155.170).
– PU + ATT (5 vs 12). The endogenous model (PU→VALUE, ATT→VALUE) was preferred by BIC: BIC12 = 84.465 < 88.701 (ΔBIC = 4.236; positive evidence). The AIC difference was negligible (33.415 < 33.724; ΔAIC = .309).
– PEU + PU + ATT (7 vs 14). The models were indistinguishable: BIC7 = BIC14 = 88.701; AIC7 = AIC14 = 33.724. With all three TAM drivers included, the data do not adjudicate the direction between VALUE and the TAM beliefs. This tie indicates observational equivalence at the level of global fit.

Taken together, four contrasts favour modelling VALUE as endogenous (especially where ATT is present), three yield exact ties, and none favours an exogenous specification. This pattern is theoretically and methodologically informative for model specification. Among the evaluated models, the evidence does not support treating VALUE as strictly exogenous. Instead, when ATT is included, the preference is strong to decisive for ATT→VALUE; when PU is included (with or without ATT), the preference is positive but more modest for PU→VALUE; and PEU offers no discriminating leverage on direction. A pragmatic synthesis is therefore to model VALUE as endogenous (at least in part) to ATT and, to a lesser extent, to PU, while acknowledging that, with PEU (and especially with all three TAM variables included), directionality cannot be adjudicated on fit alone. Accordingly, Models 8-14, which treat VALUE as endogenous to the TAM core variables, are examined in detail below.

4.6 RQ4

To address RQ4, seven endogenous-VALUE candidate path models (Models 8-14) that retain the VALUE→BI path were compared to identify the specification that best balances fit and parsimony and explains BI most effectively. All models were anchored on the TAM baseline (PEU→PU, PU→ATT, PEU→ATT, ATT→BI, PU→BI), retained the direct path VALUE→BI (consistent with RQ2), and differed only in which TAM variables were specified as predictors of VALUE (PEU, PU, ATT, singly or in combination), with VALUE modelled as endogenous to the TAM core variables (consistent with RQ3). Model evaluation considered: information criteria (BIC, AIC), global fit indices (χ^2, df, p; CFI; TLI; RMSEA with 90% CI and PCLOSE; SRMR), explained variance (R^2), and standardised direct/indirect effects (β).

Information criteria. Model comparison based on information criteria (lower is better) – BIC and AIC – identified a clear top tier comprising Model 12 and Model 14 (Tab. 2). Model 12 achieved the lowest values (BIC = 84.465; AIC = 33.415), with Model 14 close behind (BIC = 88.701; AIC = 33.724). Relative to Model 12, the differences were ΔBIC = 4.236 (positive evidence favouring Model 12) and AIC = .309 (near equivalence). A middle tier followed: Model 9 and Model 10, which were clearly inferior to Model 12 (ΔBIC = 19.088 and 24.984; ΔAIC = 23.015 and 24.984, respectively). Models 11 and 13 performed worse than 9-10 yet remained far superior to the poorest model (ΔBIC from Model 12 = 37.002 and 40.747; ΔAIC = 40.929 and 40.747, respectively). Model 8 was by far the least parsimonious (ΔBIC = 216.665, ΔAIC = 220.592 vs Model 12).

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
BIC	301.130	103.553	109.449	121.467	84.465	125.212	88.701
AIC	254.007	56.430	58.399	74.344	33.415	74.162	33.724

Tab. 2: BIC and AIC

Global fit. Global fit varied widely across Models 8-14 (CFI = .74-.995; TLI = .135-.969; RMSEA = .085-.45; SRMR = .021-.239; Tab. 3). Model 8 was clearly a poor-fitting solution. Model 13 also misfitted severely on RMSEA and TLI, despite acceptable SRMR and CFI. Intermediate fit is observed for Models 9 and 10: both improve CFI (to .966 and .965) and reduce SRMR (to .039 and .040), yet RMSEA remains elevated (.162 and .202) with TLI below .90. Model 11 displayed a similar mixed profile (CFI = .946; TLI = .820; SRMR = .049) with high RMSEA (.205). The best-fitting specifications were Models 12 and 14. Model 12 achieved CFI = .994, TLI = .969, SRMR = .021, and RMSEA = .085 ([.026, .154], PCLOSE = .131); Model 14 achieved CFI = .995, TLI = .946, SRMR = .021, and RMSEA = .112 [.038, .209], PCLOSE = .077).

Given the very low degrees of freedom (df = 1-3), RMSEA is expected to be upward-biased; accordingly, evaluation relied primarily on CFI/TLI and SRMR, and on RMSEA's 90% CI and PCLOSE, rather than a single cut-off. In any case, for Models 12 and 14, PCLOSE > .05 and the CIs include close-fit values, indicating that close fit cannot be rejected despite the elevated RMSEA point estimates. Moreover, as regards χ^2, with N = 375 and small df, χ^2 tests were – as expected – significant for all models ($p < .001$) except that Models 12 and 14, while markedly better on incremental indices, also yielded significant χ^2 (Model 12: $\chi^2(2) = 7.415$, $p = .025$; Model 14: $\chi^2(1) = 5.724$, $p = .017$). This pattern is typical under large samples and low-df structures; therefore, χ^2 was not used as the sole arbiter of fit.

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
χ^2, df, p	$\chi^2(3)$ = 230.007, p < .001	$\chi^2(3)$ = 32.430, p < .001	$\chi^2(2)$ = 32.399, p < .001	$\chi^2(3)$ = 50.344, p < .001	$\chi^2(2)$ = 7.415, p = .025	$\chi^2(2)$ = 48.162, p < .001	$\chi^2(1)$ = 5.724, p = .017
CFI	.74	.966	.965	.946	.994	.947	.995
TLI	.135	.888	.826	.820	.969	.736	.946
RMSEA CI90 PCLOSE	.45 [.402-.500] <.001	.162 [.115, .214] <.001	.202 [.144, .265] <.001	.205 [.158, .257] <.001	.085 [.026, .154] = .131	.248 [.191, .312] <.001	.112 [.038, .209] = .077
SRMR	.239	.039	.040	.049	.021	.049	.021

Tab. 3: Global fit

Explained variance (R^2). The TAM baseline explained 3.9% of PU variance ($R^2 = .039$), 66.2% of ATT variance ($R^2 = .622$), and 43.4% of BI variance ($R^2 = .434$). Across the VALUE models, patterns shifted as follows (Tab. 4). With only PEU→VALUE (Model 8), VALUE was barely explained ($R^2 = .015$), and BI dropped below the TAM baseline ($R^2 = .396$; -3.8 pp). With only PU→VALUE (Model 9), R^2 for VALUE rose sharply (.419) and BI increased to .503 (+6.9 pp); adding PEU (Model 10) produced no further gain (identical R^2). With only ATT→VALUE (Model 11), VALUE was explained to a similar degree ($R^2 = .391$), and BI reached .504 (+7 pp); adding PEU to ATT (Model 13) left results essentially unchanged (VALUE = .394; BI = .504). The combination PU→VALUE + ATT→VALUE (Model 12) yielded the highest downstream effects (VALUE = .457; BI = .515; +8.1 pp), and including PEU as well (Model 14) did not raise BI further ($R^2 = .515$), while only marginally increased VALUE ($R^2 = .459$). Across Models 8-14, R^2(PU) and R^2(ATT) remained constant and comparable to the baseline (PU = .039; ATT = .622). In sum, VALUE was a robust predictor of BI when modelled as a function of PU and ATT; adding PEU as an additional predictor of VALUE conferred no appreciable incremental contribution to VALUE and, indirectly, to BI.

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
R^2	VALUE = .015 PU = .039 ATT = .622 BI = .396	VALUE = .419 PU = .039 ATT = .622 BI = .503	VALUE = .419 PU = .039 ATT = .622 BI = .503	VALUE = .391 PU = .039 ATT = .622 BI = .504	VALUE = .457 PU = .039 ATT = .622 BI = .515	VALUE = .394 PU = .039 ATT = .622 BI = .504	VALUE = .459 PU = .039 ATT = .622 BI = .515

Tab. 4: Explained variance

Standardised direct effects (β). The TAM core paths were stable across models (see Tab. 5): PEU→PU (.199), PEU→ATT (.137), PU→ATT (.750), PU→BI (.173-.193), ATT→BI (.249-.278). Across Models 8-14, the TAM core paths not involving BI were identical to the baseline (Tab. 5): PEU→PU = .199; PEU→ATT = .137; PU→ATT = .750. By contrast, the direct effects on BI were attenuated relative to the TAM baseline (PU→BI = .331; ATT→BI = .368): in the VALUE models, PU→BI ranged from .173 to .193 and ATT→BI from .249 to .278. This attenuation was consistent with VALUE capturing part of the variance previously attributed to PU and ATT. The direct VALUE→BI path remained large and statistically significant across all specifications, ranging from .386 to .431, with non-overlap of the 95% bootstrap confidence intervals with zero (see Tab. 5).

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
PEU→PU	.199*** [.094, .299]	.199*** [.094, .299]	.199*** [.094, .299]	.199*** [.094, .299]	.199*** [.094, .299]	.199*** [.094, .299]	.199*** [.094, .299]
PEU→ATT	.137*** [.072, .205]	.137*** [.072, .205]	.137*** [.072, .205]	.137*** [.072, .205]	.137*** [.072, .205]	.137*** [.072, .205]	.137*** [.072, .205]
PU→ATT	.750*** [.686, 803]	.750*** [.686, 803]	.750*** [.686, 803]	.750*** [.686, 803]	.750*** [.686, 803]	.750*** [.686, 803]	.750*** [.686, 803]
PU→BI	.193** [.009, .384]	.175** [.008, .346]	.175** [.008, .346]	.175** [.008, .346]	.173** [.008, .344]	.175** [.008, .346]	.173** [.008, .344]
ATT→BI	.278*** [.140, .425]	.252*** [.126, .390]	.252*** [.126, .390]	.252*** [.126, .390]	.249*** [.126, .383]	.252*** [.126, .390]	.249*** [.126, .383]
PEU→VALUE	.122* [.001, .239]	.647*** [.557, 729]	-.007 [-.088, .083]	-	-	-.062 [-.148, .033]	-.052 [-.131, .036]
PU→VALUE	-	-	.649*** [.552, .735]	.625*** [.550, 693]	.408*** [.245, .554]	-	.405*** [.242, 552]
ATT→VALUE	-	-	-	-	.308*** [.186, .438]	.643*** [.560, .714]	.325*** [.197, .457]
VALUE→BI	.431*** [.269, .551]	.391*** [.247, 504]	.391*** [.246, 504]	.390*** [.240, .500]	.386*** [.244, .496]	.390*** [.248, .500]	.386*** [.244, .496]

Tab. 5: Standardised direct effects[6]

Standardised indirect effects (β). As shown in Tab. 6, the PU→ATT→BI pathway remained the largest TAM-consistent indirect component across VALUE models (β = .187-.209), albeit smaller than in the TAM baseline (β = .276) – a reduction consistent with part of PU's influence operating through VALUE-mediated chains. When PU predicted VALUE, the largest VALUE-mediated components were PU→VALUE BI (up to β = .254) and PU ATT→VALUE BI (up to β = .188). When ATT predicted VALUE, ATT→VALUE BI was also sizeable (up to β = .251). By contrast, VALUE routes involving PEU were small and occasionally

6 The reported direct effects are standardised (β). Standardised coefficients are reported with *p*-values from ML estimation with the following meaning: *** p < .001, ** p < .01, * p < .05. 95% bootstrap confidence intervals (percentile method, B = 5000) are shown in brackets.

negative (e.g., PEU→VALUE→BI from -.024 to .053; PEU→PU→VALUE→BI up to .050; PEU→ATT→VALUE→BI up to .034; PEU→PU→ATT→VALUE→BI up to .037). Overall, VALUE exerted a meaningful mediated influence primarily when it was modelled as being predicted by PU and/or ATT. In contrast, PEU-based VALUE routes were weak, offering little incremental contribution beyond PU and ATT.

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
PU→ATT→BI	.209	.189	.189	.189	.187	.189	.187
PEU→ATT→BI	.038	.035	.035	.035	.034	.035	.034
PEU→PU→BI	.038	.035	.035	.035	.034	.035	.034
PEU→PU→ATT→BI	.041	.038	.038	.038	.037	.038	.037
PEU→VALUE→BI	.053			-.003			-.024
PEU→PU→VALUE→BI		.05	.05		.031		
PEU→ATT→VALUE→BI				.033	.016	.034	.017
PEU→PU→ATT→VALUE→BI				.036	.018	.037	.019
PU→VALUE→BI		.253	.254		.157		.156
PU→ATT→VALUE→BI				.183	.089	.188	.094
ATT→VALUE→BI				.244	.119	.251	.125

Tab. 6: Standardised indirect effects[7]

Model retention. Based on BIC and AIC, Model 12 emerged as the best-fitting specification, with Model 14 a close alternative; all other candidates were decisively disfavoured. Global-fit indices (CFI/TLI, SRMR, and RMSEA 90% CIs/PCLOSE) likewise supported retaining Model 12, with Model 14 acceptable as a sensitivity alternative. Both Model 12 and Model 14 achieved the highest explained variance in BI (R^2 = .515, i.e., +8.1 pp over the TAM baseline), with only marginal differences for VALUE (R^2 = .457 vs .459). Standardised effects indicated a large VALUE→BI path ($\beta \approx .39$), attenuated PU→BI and ATT→BI relative to the baseline, sizeable VALUE-mediated components via PU/ATT, and small/negligible PEU-based routes.

4.7 Final model selection and retained specification

Given the inconclusive evidence in RQ3 regarding the role of PEU relative to VALUE, an additional specification was estimated alongside the two leading candidates. Model 15 treated PEU as downstream of VALUE (VALUE→PEU) while retaining PU→VALUE and ATT→VALUE; this was compared with Model 12 (no PEU-VALUE link; PU→VALUE, ATT→VALUE) and Model 14 (PEU→VALUE plus PU→VALUE, ATT→VALUE). All models were anchored on the TAM baseline and retained VALUE→BI.

The comparison between the models yielded the following results (Tab. 7). By information criteria, Model 12 remained preferred (BIC = 84.465; AIC = 33.415), with Models 14 and 15 tied and slightly worse (BIC = 88.701; AIC = 33.724; ΔBIC vs Model 12 = 4.236; ΔAIC = 0.309). Global-fit indices were consistent: Model 12 achieved lower RMSEA (.085 vs .112) and higher TLI (.969 vs .946), with CFI and SRMR essentially identical (.994-.995; .021). RMSEA 90% CIs and PCLOSE favoured Model 12 (.131 vs .077). Across the three candidates, BI was identical (R^2 = .515), while VALUE differed only trivially (R^2 = .456-.459); PU and ATT were essentially unchanged (R^2 = .036-.039 and .621-.622, respectively). In Model 15, the variance accounted for in PEU was effectively nil (reported as $R^2 \approx 0$).

Allowing PEU to be either upstream of VALUE (Model 14) or downstream of VALUE (Model 15)

7 The reported indirect effects are standardised (β).

did not improve fit over the more parsimonious Model 12. Accordingly, the final retained specification models VALUE as predicted by PU and ATT, includes VALUE→BI, and does not introduce an additional PEU-VALUE linkage beyond the standard TAM paths (PEU→PU, PEU→ATT). This resolves the PEU-VALUE placement without adding complexity and supports focusing subsequent interpretation on the PU/ATT→VALUE BI nexus. Notably, Model 15 explained no variance in PEU, and did not increase R^2(BI) relative to Models 12 and 14, further arguing against retaining any additional PEU-VALUE linkage.

In conclusion, considering fit, parsimony, and explanatory power, Model 12 was retained as the preferred specification. It yielded the lowest BIC/AIC (84.465/33.415), higher TLI (.969) and lower RMSEA (.085; 90% CI [.026, .154], PCLOSE = .131) with CFI and SRMR of .994 and .021 respectively, and matched the highest R^2(BI) = .515 (+8.1 pp over the TAM baseline). Models 14 and 15 were near equivalent on CFI/SRMR but did not improve information criteria (ΔBIC = 4.236; ΔAIC = .309) or R^2(BI); Model 15 also explained essentially no variance in PEU (adjusted $R^2 \approx 0$). There is therefore no empirical justification to introduce a PEU-VALUE linkage.

Retained model (Model 12; Fig. 2): baseline TAM paths PEU→PU, PEU→ATT, PU→ATT, ATT→BI, PU→BI; plus PU→VALUE and ATT→VALUE; with VALUE→BI.

	Model 15	**Model 12**	**Model 14**
AIC	33.724	33.415	33.724
BIC	88.701	84.465	88.701
χ^2, df, p	$\chi^2(1) = 5.724$, p = .017	$\chi^2(1) = 7.415$, p = .025	$\chi^2(1) = 5.724$, p = .017
CFI	.995	.994	.995
TLI	.946	.969	.946
RMSEA CI90 PCLOSE	.112 [.038, .209] = .077	.085 [.026, .154] = .131	.112 [.038, .209] = .077
SRMR	.021	.021	.021
R^2	VALUE = .456 PEU ≈ 0[8] PU = .036 ATT = .621 BI = .515	VALUE = .457 PU = .039 ATT = .622 BI = .515	VALUE = .459 PU = .039 ATT = .622 BI = .515

Tab. 7: Comparison of Models 12, 14, and 15 – information criteria, global fit, and explained variance

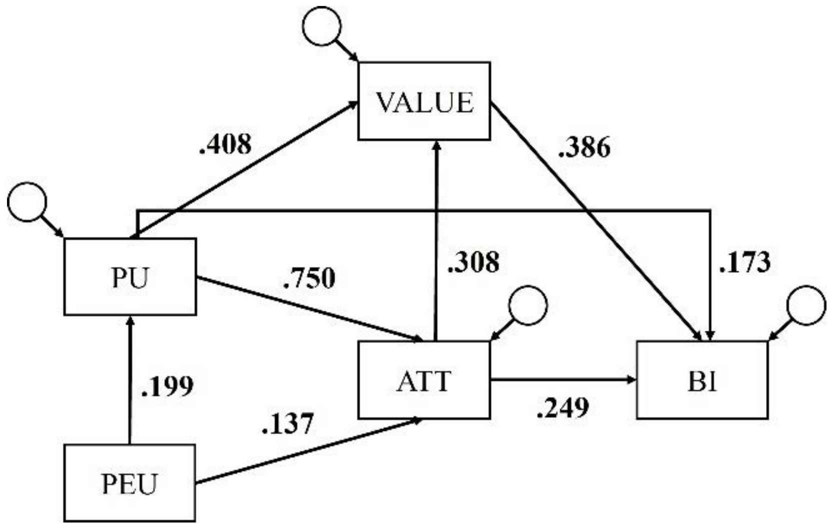

Fig. 2: Model 12 – Structural path diagram with standardised direct effects

8 SPSS AMOS reported -.034 for PEU. Negative adjusted R² values can occur and indicate no explained variance; for interpretability, the value is truncated to 0.

5. Discussion and conclusions

The present study shows that teachers' value beliefs about technology (VALUE) substantially enhance the prediction of their intention to use them (BI), over and above the TAM core constructs (PEU, PU, and ATT). Adding VALUE to a baseline TAM model increased the explained variance in BI from about 44% to 52% – medium effect (RQ1). This means that beyond the traditional TAM factors, the extent to which teachers believe that technology is an important and beneficial tool for teaching and learning is a unique and powerful driver of their willingness to integrate it. Notably, the influence of VALUE on intention was predominantly direct rather than operating solely through PU or ATT: across multiple model comparisons, including a direct path from VALUE to BI, provided a decisively better fit than models where VALUE operated solely via TAM's existing pathways (RQ2). This pattern aligns with evidence that value beliefs are a distinct and proximal driver of technology adoption in educational settings (e.g., Cheng et al., 2020; Vongkulluksn et al., 2018; Vongkulluksn et al., 2020).

Results from RQ3 indicated that VALUE is best conceptualised, at least in part, as endogenous to the TAM core variables: specifically, downstream of ATT and, to a lesser extent, downstream of PU. At the same time, the direction relative to PEU remained indeterminate (ties in model fit). Substantively, this suggests that teachers' value beliefs may crystallise from their broader attitudinal stance and perceived usefulness and once formed, exert a sizeable direct influence on intention. This interpretation is consistent with Situated Expectancy-Value Theory (SEVT), which frames value as a situated, experience-sensitive construct shaped by contextual feedback and success experiences rather than a fixed exogenous trait (Eccles & Wigfield, 2020). A plausible mechanism is that positive experiences and training improve ATT and PU, which in turn consolidate a stronger sense that technology is valuable for one's teaching. SEVT explicitly anticipates such dynamics, as values are updated through experience and perceived effectiveness.

Finally, the favoured specification (Model 12: PEU®PU, PEU®ATT, PU®ATT, ATT®BI, PU®BI; PU®VALUE, ATT®VALUE; VALUE®BI; no PEU-VALUE linkage) positions VALUE downstream of ATT (and modestly PU) and upstream of BI. Two theoretical and practical implications follow. Theoretically, first, VALUE is not a peripheral add-on but a central, proximal predictor that meaningfully boosts the variance explained in intentions beyond the TAM core variables. Second, directionality analyses argue for treating VALUE as at least partly endogenous to the TAM network in teacher populations – especially along ATT→VALUE – thereby integrating the TAM's cognitive-affective core with SEVT's account of values as situated and malleable.

Practically, for designing teacher education and professional development, the findings argue for two complementary levers. First, strengthen PU and ATT by, for instance, emphasising importance and utility, managing perceived costs such as time, and providing credible evidence of gains in job performance (to raise PU), alongside facilitating scaffolded success experiences (to bolster ATT). These same experiences are also likely to build value beliefs endogenously, which, in turn, directly strengthen the intention to use. Second, cultivate VALUE directly by designing technology-mediated, authentic, curriculum-aligned tasks and learner-centred scenarios that make instructional value visible, and by prompting structured reflection grounded in credible evidence of positive impact on teaching and learning. For instance, this can be achieved by embedding utility-value activities in which teachers explicitly articulate why and how a given digital tool serves specific instructional goals; by designing curriculum-aligned tasks with explicit success criteria that make the instructional benefits observable (e.g., improved lesson orchestration and teaching efficiency, stronger student engagement, clearer progress towards learning goals, and gains in student learning); and by prompting evidence-informed reflection using concrete classroom artefacts and indicators (e.g., work samples, participation/engagement data) to appraise impact. A proposal that aligns with these levers can be found in Foschi (2023). The paper presents a design and a concrete example – realised with lower and upper secondary school teachers – of training activities on the educational use of digital technologies, detailing planning (guided by Backward Design), implementation (drew on features of effective continuous professional development: active learning, collaboration, use of models and modelling of effective practices, expert support and coaching, feedback and reflection, sustained duration, focus on disciplinary content; and congruent teaching), and evaluation (multi-level, multi-method, and inspired by Guskey's model).

Overall, the study extends the TAM by demonstrating that, for both pre-service and in-service teachers, believing that the use of digital technologies for teaching and learning is valuable is not ancillary but a central determinant of technology acceptance – one that directly and substantially strengthens intention to integrate technology in the classroom, while itself being shaped by attitudes and, to a lesser extent, perceived usefulness. Nevertheless, several limitations warrant caution. First, the analyses rely on cross-sectional path models using observed mean-composite scores, which constrains causal inference and precludes explicit modelling of measurement error. Second, the study draws on a convenience sample and self-reports, raising concerns about generalisability and common-method bias. Finally, with limited degrees of freedom, some global-fit indices (e.g., RMSEA) are known to be unreliable; cut-off rules should be interpreted contextually rather than mechanically.

Future work should strengthen inference and scope in at least three ways. Measurement and estimation: move from composites to latent-variable SEM, establish reliability at the latent level, and test measurement invariance across pre-service vs in-service teachers. Design: implement longitudinal, multi-wave studies that test reciprocal, time-ordered influences among VALUE, ATT, and PU. Outcomes and data sources: complement BI with behavioural indicators of use (e.g., classroom observations) and multi-informant data (e.g., school principals, students). Collectively, these steps would enhance the findings' generalisability, sharpen causal interpretability, and increase practical relevance, clarifying when – and for whom – VALUE most powerfully drives teachers' technology-integration intentions and behaviours.

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Appendix

	Paths specification*	BIC	AIC
Model 1	VALUE→PEU, VALUE→BI	301.130	254.007
Model 2	VALUE→PU, VALUE→BI	109.449	58.399
Model 3	VALUE→PEU, VALUE→PU, VALUE→BI	109.449	58.399
Model 4	VALUE→ATT, VALUE→BI	280.382	229.332
Model 5	VALUE→PU, VALUE→ATT, VALUE→BI	88.701	33.724
Model 6	VALUE→PEU, VALUE→ATT, VALUE→BI	280.382	229.332
Model 7	VALUE→PEU, VALUE→PU, VALUE→ATT, VALUE→BI	88.701	33.724
Model 8	PEU→VALUE, VALUE→BI	301.130	254.007
Model 9	PU→VALUE, VALUE→BI	103.553	56.430
Model 10	PEU→VALUE, PU→VALUE, VALUE→BI	109.449	58.399
Model 11	ATT→VALUE, VALUE→BI	121.467	74.344
Model 12	PU→VALUE, →VALUE, VALUE→BI	84.465	33.415
Model 13	PEU→VALUE, ATT→VALUE, VALUE→BI	125.212	74.162
Model 14	PEU→VALUE, PU→VALUE, ATT→VALUE, VALUE→BI	88.701	33.724
Model 15	VALUE→ PEU, PU→VALUE, ATT→VALUE, VALUE→BI	88.701	33.724

Tab. 8. Model comparison: BIC and AIC[9]

9 *All models are nested within the TAM baseline: PU→ATT, PU→BI, PEU→PU, PEU→ATT, ATT→BI.