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Determinants Of Accounting Students' Intention To Learn Blockchain Technology: An Extended UTAUT2 Model

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Abstract

This study examines the determinants of accounting students' intention to learn blockchain technology, an issue that remains empirically underexplored even though blockchain is projected to transform accounting practice within the coming decade. Whereas prior research on blockchain adoption has concentrated on practitioners who already interact with the technology, the perspective of students as the future pipeline of the accounting profession, particularly in developing countries, has received limited attention. Building on an extension of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) that incorporates a technology awareness construct, the study assesses how five determinants shape learning intention. Responses from 125 accounting students, obtained through an online seven-point Likert questionnaire, were examined with partial least squares structural equation modeling (PLS-SEM), and the model accounts for 53.1% of the variance in learning intention. Four determinants are positive and significant, with effort expectancy as the strongest predictor, whereas facilitating conditions exert a significant but negative effect. The findings validate an extended UTAUT2 for anticipatory technology adoption and inform the design of responsive digital accounting curricula.

Keywords: blockchain technology, learning intention, UTAUT2, technology awareness, accounting education.

INTRODUCTION

The accounting profession is undergoing the most fundamental digital transformation in more than a century. Among the disruptive technologies now emerging,

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blockchain stands out as an innovation with the potential to redefine the foundations of accounting itself, from a triple-entry system that supplements traditional double-entry bookkeeping to continuous auditing that removes the information lag long characteristic of audit practice (Bonsón & Bednárová, 2019; Han et al., 2023). Its core characteristics of decentralization, immutability, on-chain transparency, and automation through smart contracts position it as a digital trust infrastructure capable of substantially improving the reliability, accountability, and efficiency of financial reporting (Dashkevich et al., 2024; Nakamoto, 2008).

Although the potential of blockchain has long been praised in the literature, its benefits will not be realized without one crucial precondition: the willingness of the next generation of accounting professionals to learn, understand, and integrate the technology into their practice. In an in-depth study of the barriers to blockchain adoption in accounting, Akter et al. (2024) identify a lack of knowledge as one of the most fundamental obstacles; the constraint is not a technological or regulatory limitation but a competence gap among potential users. This finding places universities, as the primary producers of accounting graduates, in a strategic position to bridge the gap (Pimentel & Boulianne, 2020; Şahin & Kurniawan, 2025).

In Indonesia, however, the integration of blockchain into accounting curricula remains very limited. This raises a strategic question: to what extent do Indonesian accounting students intend to learn blockchain, and which factors shape that intention? The question is not trivial, because students occupy what Karahanna et al. (1999) describe as a pre-adoption phase, in which individuals evaluate a technology on the basis of conceptual information and career projections rather than direct usage experience. This notion of anticipatory technology adoption carries an important implication: learning intention forms before any real contact with the technology and therefore calls for a conceptual frame that differs from adoption studies conducted on actual users.

The existing literature reveals several significant empirical gaps. First, most research on blockchain adoption in accounting focuses on practitioners who have already interacted with blockchain systems. Applying an extended UTAUT model to 329 accountants and auditors in Jordan, Alkhwaldi et al. (2024) reported that adoption intention was significantly shaped by performance expectancy and social influence, whereas effort expectancy unexpectedly had no significant effect. This outcome raises the question of whether a similar pattern would appear among students who do not possess the technical background of practitioners. Second, Şahin & Kurniawan (2025), through a comprehensive bibliometric review, document the scarcity of quantitative

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empirical studies on blockchain accounting in Southeast Asia. Third, the two most relevant Indonesian studies, Handoko & Lantu (2020) on auditors and Rani & Pratolo (2024) on the institutional readiness of private universities, do not address the perspective of accounting students. The individual perspective of students as the supply pipeline of the Indonesian accounting profession thus remains an empirical gap that warrants investigation.

To address this gap, the present study draws on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) developed by Venkatesh et al. (2012) and extends it with a technology awareness construct rooted in the Technology Readiness Index (Parasuraman, 2000), because in an anticipatory adoption context the level of students' awareness of a technology is a cognitive precondition for forming a meaningful intention. The study tests the effects of five determinants, namely performance expectancy, effort expectancy, social influence, facilitating conditions, and technology awareness, on the intention to learn blockchain among accounting students in Indonesia. The study contributes to the literature in three ways. Theoretically, it extends UTAUT2 with technology awareness and validates it in an anticipatory technology-adoption context that has been little explored. Methodologically, it responds to the explicit call by Akter et al. (2024) for quantitative validation of blockchain adoption factors through a PLS-SEM approach in a different geographical setting. Practically, its findings provide an empirical basis for Indonesian universities to design digital accounting curricula that are responsive to the needs of industry transformation.

LITERATURE REVIEW

Scholarship on technology acceptance has advanced across a series of model generations. Foundational frameworks, among them the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (Ajzen, 1991), clarified the way attitudes, social norms, and behavioral control drive intention, whereas Davis (1989) distilled these ideas, through the Technology Acceptance Model, into two central beliefs: usefulness and ease of use. Venkatesh et al. (2003) merged eight preceding models into the Unified Theory of Acceptance and Use of Technology (UTAUT); its four pillars, namely performance expectancy, effort expectancy, social influence, and facilitating conditions, together explained close to 70% of behavioral-intention variance. A subsequent refinement, UTAUT2 (Venkatesh et al., 2012), was tailored to consumer and voluntary contexts and brought in three further constructs, namely hedonic motivation, price value, and habit, raising explained variance to 74%. Because accounting students voluntarily

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choose to learn blockchain, the present study adopts the four core UTAUT2 constructs, omits the three additional constructs as less relevant to anticipatory student adoption, and adds technology awareness as a fifth determinant.

Performance Expectancy

Framed by Venkatesh et al. (2003) as a person's belief that a system will improve their job performance, performance expectancy carries forward the perceived-usefulness idea of the Technology Acceptance Model (Davis, 1989) and has repeatedly ranked among the most decisive antecedents of intention. In the blockchain accounting context, this pattern has been confirmed by Alkhwaldi et al. (2024) and Al-Hattami et al. (2024). For accounting students in the process of forming a professional identity, the evaluation of career-relevant benefits is a meaningful basis for intention. Accordingly, the first hypothesis is proposed.

H1: Performance expectancy positively affects the intention to learn blockchain technology.

Effort Expectancy davis

Traceable to perceived ease of use (Davis, 1989), effort expectancy captures how effortless a system is to operate (Venkatesh et al., 2003); the more effortless the technology seems, the weaker the psychological barriers to intention become. Alkhwaldi et al. (2024) found effort expectancy to be non-significant among practitioners, arguing that experienced professionals focus on functional benefits rather than the effort of learning. Whether this pattern also applies to students is an open question. Karahanna et al. (1999) show that in the pre-adoption phase the evaluation of ease of learning plays an important role because individuals lack direct experience to validate their beliefs, and Novak et al. (2022) note that the technical complexity of blockchain can pose a substantial cognitive barrier for accounting students without a computer-science background.

H2: Effort expectancy positively affects the intention to learn blockchain technology.

Social Influence

For Venkatesh et al. (2003), social influence reflects how strongly a person senses that people who matter to them expect them to take up a system; the construct folds in the subjective norm from both the Theory of Reasoned Action (Fishbein & Ajzen, 1975) and the Theory of Planned Behavior (Ajzen, 1991). Venkatesh et al. (2012) emphasize

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that social influence remains relevant in voluntary contexts, where individuals rely on external social cues under uncertainty. In the collectivist Indonesian academic environment, characterized by high power distance (Hofstede, 1980), the views of lecturers, peers, and professional associations carry considerable weight, and the significance of social influence in blockchain accounting has been confirmed by Al-Hattami & H. M. (2024) and Alkhwaldi et al. (2024).

H3: Social influence positively affects the intention to learn blockchain technology.

Facilitating Conditions

Anchored in perceived behavioral control (Ajzen, 1991), facilitating conditions indicate how far a person judges the support and resources needed to run a system to be within reach (Venkatesh et al., 2003). In the student context, facilitating conditions are best operationalized as learning support, including the availability of quality learning materials, competent lecturers, training facilities, and academic assistance. Tarhini et al. (2017) show that facilitating conditions are a strong predictor of educational technology adoption in developing countries where institutional support varies widely, and Desplebin et al. (2025) note that higher-education institutions are still at an early and uneven stage of integrating blockchain into their curricula.

H4: Facilitating conditions positively affect the intention to learn blockchain technology.

Technology Awareness

Technology awareness, the fifth determinant, is defined as the level of an individual's knowledge, understanding, and exposure to a technology (Karahanna et al., 1999; Parasuraman, 2000). Drawing on the Technology Readiness Index, Parasuraman (2000) establishes that awareness is a core element of readiness to adopt new technologies, while Karahanna et al. (1999) maintain that conceptual knowledge serves as a legitimate basis for intention during the pre-adoption phase, since a person cannot form a meaningful intention toward a technology they do not yet know. Akter et al. (2024) identify a lack of knowledge as a key barrier to blockchain adoption in accounting, supporting the relevance of technology awareness as an explicit construct.

H5: Technology awareness positively affects the intention to learn blockchain technology.

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The dependent variable, the intention to learn blockchain, is conceptually distinguished from the intention to use. Because accounting students are in a pre-adoption phase (Karahanna et al., 1999), learning intention is defined as the psychological tendency of students to allocate cognitive effort, time, and resources to mastering blockchain technology in accounting practice, formed on the basis of conceptual information rather than actual use. The five hypothesized relationships are summarized in the research model in Figure 1.

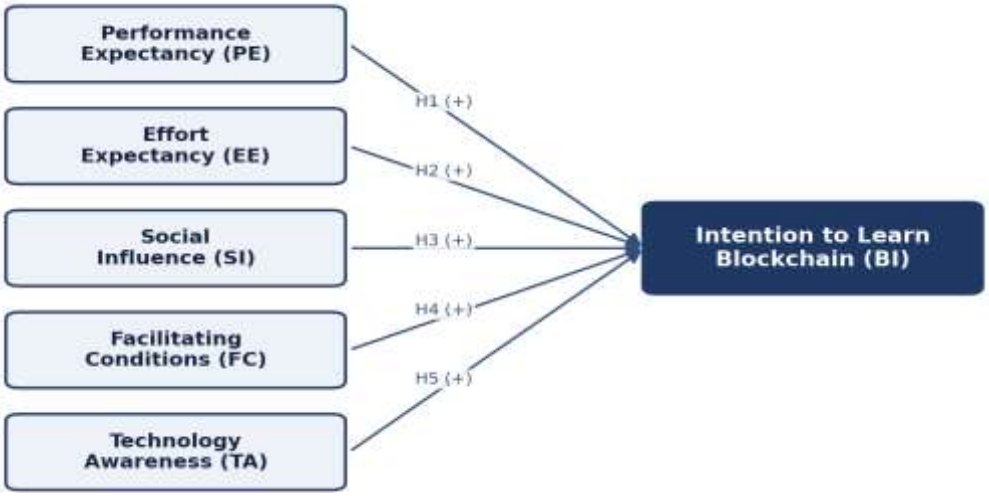


Figure 1. Research Model

RESEARCH METHOD

A quantitative, cross-sectional design underpins this research. Its target population is students enrolled in accounting programs at higher-education institutions throughout Yogyakarta, Indonesia. A sample of 105 students was selected through purposive sampling, with the main criteria being active undergraduate accounting students who had completed at least their third semester and were willing to participate voluntarily. Selecting respondents from the third semester onward ensures that they had taken foundational accounting courses and thus possessed a frame of reference for evaluating the relevance of blockchain to accounting practice. In line with the PLS-SEM guidelines of Hair et al. (2019), the sample meets the minimum threshold of ten times the greatest number of structural paths pointing to any single construct.

Primary data were compiled over roughly two months through a self-administered questionnaire circulated on Google Forms. The instrument comprises 22 items measuring one dependent variable, the intention to learn blockchain (BI), and five independent

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variables, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and technology awareness (TA). Each item was drawn from previously validated instruments and slightly recontextualized for blockchain accounting learning, with answers recorded on a seven-point scale anchored at 1 for strong disagreement and 7 for strong agreement.

The framework tested is UTAUT2 extended with technology awareness, in which the five independent variables directly affect the dependent variable, expressed as BI = β1PE + β2EE + β3SI + β4FC + β5TA + ε. Data were analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4 (Ringle et al., 2024). PLS-SEM was chosen because of the exploratory and predictive aim of the study, the addition of a new construct to an established model, the moderate sample size, and data that do not require the assumption of normal distribution (Hair et al., 2019).

The analysis unfolded across two phases. The outer (measurement) model was appraised first against four benchmarks: every indicator loading had to reach 0.70; both composite reliability and Cronbach's alpha had to attain 0.70 for internal consistency; the average variance extracted (AVE) had to be no lower than 0.50 for convergent validity; and the Heterotrait-Monotrait ratio (HTMT) had to remain under 0.85 for discriminant validity (Henseler et al., 2015). The structural (inner) model was then evaluated through a bootstrapping routine of 5,000 subsamples to derive path coefficients, t-statistics, and p-values, supplemented by the coefficient of determination, effect size, and out-of-sample predictive relevance via the PLSpredict procedure (Shmueli et al., 2019). A hypothesis receives support when its path coefficient carries a positive sign, its t-statistic exceeds 1.96, and its p-value falls below 0.05. Data credibility is established through the convergent validity, discriminant validity, and reliability tests reported below.

RESULTS

The 105 responses were complete and usable for analysis. Table 1 presents the descriptive statistics at the construct level, computed from the mean score of the indicators of each construct on the seven-point scale.

Table 1. Descriptive Statistics of Constructs

Construct	Mean	Std. Deviation	Min–Max
Performance Expectancy (PE)	5.767	1.148	2.25–7.00

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Construct	Mean	Std. Deviation	Min–Max
Effort Expectancy (EE)	5.938	1.113	2.75–7.00
Social Influence (SI)	5.689	1.074	2.33–7.00
Facilitating Conditions (FC)	4.438	1.367	1.00–7.00
Technology Awareness (TA)	5.762	1.056	2.67–7.00
Intention to Learn Blockchain (BI)	4.502	1.536	2.00–6.75

Table 1 reveals a notable pattern. The four antecedent constructs, effort expectancy (5.938), performance expectancy (5.767), technology awareness (5.762), and social influence (5.689), fall in the high category, indicating that most students perceive blockchain as useful, relatively easy to learn, already familiar, and socially encouraged. In contrast, facilitating conditions has the lowest mean (4.438) and the largest standard deviation (1.367), indicating that the availability of blockchain learning support is perceived as only moderate and varies widely across students. Learning intention is also moderate (4.502). This contrast between high perceived benefit and awareness on the one hand and moderate intention and institutional support on the other provides a relevant backdrop for the hypothesis testing that follows. This gap between belief and intention deserves closer attention, because it is not a pattern the acceptance literature would automatically predict. On the seven-point scale, the antecedent constructs cluster tightly between 5.689 and 5.938, yet learning intention trails almost a full scale point behind at 4.502, and it also carries the widest dispersion of any construct (SD = 1.536). Two readings are plausible. The first is attitudinal: students may recognise the value and accessibility of blockchain in the abstract while remaining uncommitted to investing their own time in mastering it, a hesitation consistent with the anticipatory nature of a pre-adoption setting in which intention is not yet reinforced by curricular obligation or workplace demand. The second is structural: the large dispersion in learning intention suggests that the sample is not uniform but divides into a more motivated segment and a more reluctant one. This heterogeneity, rather than a uniformly moderate stance, is what

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the mean of 4.502 conceals, and it frames the determinant analysis that follows as an attempt to explain what separates the two groups.

Measurement Model

In the initial estimation, two facilitating conditions indicators (FC2 and FC4) had loading factors well below 0.70 and reduced the construct's AVE below 0.50. These indicators were therefore removed to satisfy convergent validity, so that facilitating conditions in the final model is represented by two indicators (FC1 and FC3), and the final model comprises 20 indicators. The loading factors, Cronbach's alpha, composite reliability, and AVE appear in Table 2. Since each loading surpasses 0.70, each AVE surpasses 0.50, and each reliability coefficient surpasses 0.70, both convergent validity and internal consistency reliability are met.

Table 2. Convergent Validity and Reliability

Construct	Item	Loading	Cronbach's α	CR (ρc)	AVE
Performance Expectancy (PE)	PE1	0.874	0.909	0.936	0.785
	PE2	0.883			
	PE3	0.880			
	PE4	0.907			
Effort Expectancy (EE)	EE1	0.864	0.899	0.929	0.766
	EE2	0.873			
	EE3	0.884			
	EE4	0.879			
Social Influence (SI)	SI1	0.857	0.849	0.907	0.766
	SI2	0.888			
	SI3	0.880			
Facilitating Conditions (FC)	FC1	0.957	0.828	0.917	0.847
	FC3	0.882			
Technology Awareness (TA)	TA1	0.899	0.849	0.908	0.767
	TA2	0.850			
	TA3	0.877			

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Construct	Item	Loading	Cronbach's α	CR (ρc)	AVE
Intention to Learn Blockchain (BI)	BI1	0.927	0.944	0.959	0.855
	BI2	0.901			
	BI3	0.922			
	BI4	0.949			

Three checks were used for discriminant validity: the HTMT criterion, the Fornell-Larcker criterion, and an inspection of cross-loadings. Table 3 shows that every HTMT value sits comfortably under 0.85, the largest being 0.537 between facilitating conditions and learning intention. In Table 4, the square root of each construct's AVE exceeds that construct's correlations with the others, satisfying Fornell-Larcker, while each indicator loads most strongly on the construct it is meant to capture. Discriminant validity is therefore established. One salient feature of the latent-variable correlations is that facilitating conditions correlates negatively with all other constructs, including a fairly strong negative correlation with learning intention (−0.499), which foreshadows the result of the fourth hypothesis.

Table 3. Discriminant Validity — Heterotrait-Monotrait Ratio (HTMT)

	BI	EE	FC	PE	SI
EE	0.496				
FC	0.537	0.229			
PE	0.414	0.124	0.308		
SI	0.346	0.108	0.338	0.109	
TA	0.435	0.127	0.322	0.154	0.201

Table 4. Discriminant Validity — Fornell-Larcker Criterion
Structural Model and Hypothesis Testing

	BI	EE	FC	PE	SI	TA
BI	0.925					
EE	0.465	0.875				
FC	−0.499	−0.183	0.920			

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	BI	EE	FC	PE	SI	TA
PE	0.387	0.109	−0.273	0.886		
SI	0.316	0.096	−0.306	0.001	0.875	
TA	0.395	0.088	−0.294	0.124	0.154	0.876

Collinearity poses no problem, as every inner-model variance inflation factor remains under 1.30. The coefficient of determination (R^2) for learning intention is 0.531 (adjusted R^2 = 0.507), indicating that the five determinants jointly explain 53.1% of the variance in the intention to learn blockchain, a moderate to substantial level (Hair et al., 2019). The out-of-sample predictive relevance is confirmed by a Q^2predict of 0.481 for the construct. The model also shows an acceptable fit, with a standardized root mean square residual (SRMR) of 0.071, below the 0.08 threshold (Henseler et al., 2015). Table 5 presents the results of the hypothesis testing based on 5,000 bootstrap subsamples.

Table 5. Structural Model and Hypothesis Testing

Hyp.	Path	β	t-value	p-value	f²	Decision
H1	PE → BI	0.252	4.113	< 0.001	0.123	Supported
H2	EE → BI	0.356	6.577	< 0.001	0.259	Supported
H3	SI → BI	0.171	2.447	0.014	0.056	Supported
H4	FC → BI	−0.243	2.636	0.008	0.097	Not supported
H5	TA → BI	0.235	3.415	< 0.001	0.107	Supported

The data support four of the five hypotheses. Performance expectancy (β = 0.252), effort expectancy (β = 0.356), social influence (β = 0.171), and technology awareness (β = 0.235) each exert a positive, significant influence on learning intention, with effort expectancy the dominant predictor and the largest effect size (f^2 = 0.259). Hypothesis H4 is not supported: facilitating conditions has a statistically significant effect (t = 2.636; p = 0.008) but in a negative direction (β = −0.243), contrary to the hypothesized positive direction. A PLSpredict analysis further reveals that, across all four indicators of learning intention, the PLS-SEM root mean square error falls below that of the naïve linear benchmark, signaling high predictive power (Shmueli et al., 2019); moreover, a cross-validated predictive ability test verifies that the model significantly surpasses both the

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indicator-average benchmark (t = 6.101; p < 0.001) and, at the construct level, the linear-model benchmark (t = 2.505; p = 0.014). Taken as a whole, the structural results describe a model that is both explanatory and predictive without being complete. The 53.1 percent of variance accounted for, together with a Q^2predict of 0.481 and the model's consistent advantage over the naïve benchmarks, indicates that the five determinants capture a substantial and generalisable portion of what shapes learning intention in this population. At the same time, close to half of the variance remains unexplained, which is itself informative: it signals that the intention to learn an emerging technology in a pre-adoption phase is driven only in part by the perceptual factors UTAUT foregrounds, leaving room for dispositional influences such as individual innovativeness or risk tolerance, and for contextual influences such as labour-market signals specific to the Indonesian accounting profession. The pattern of significant paths sharpens this reading further. That four of the five determinants matter, but that the strongest of them concerns the ease of learning rather than the rewards of use, locates the decisive action at the very front of the adoption journey, where students are still deciding whether the effort of engagement is worth undertaking at all. It is against this backdrop that the individual hypotheses are interpreted below.

DISCUSSION

The findings support the relevance of an extended UTAUT2 model for explaining accounting students' intention to learn blockchain in a pre-adoption context. The support for H1 is consistent with the UTAUT tradition that positions performance expectancy as a primary predictor of intention (Venkatesh et al., 2003, 2012) and confirms the findings of Alkhwaldi et al. (2024) and Al-Hattami & H. M. (2024) in the blockchain accounting context. Students appear to form their learning intention on the basis of the projected benefits of blockchain mastery for their professional competence and competitiveness in the labor market, reflecting the cognitive evaluation of career-relevant outcomes characteristic of the professional identity-formation stage.

The support for H2, with effort expectancy as the strongest predictor, provides a direct answer to the question raised in the hypothesis development. Whereas Alkhwaldi et al. (2024) found effort expectancy to be non-significant among practitioners, the present study finds the opposite for students. For learners who do not yet possess adequate technology literacy, the perceived ease of learning becomes the most decisive consideration. This result is consistent with the argument of Karahanna et al. (1999) that ease-of-learning evaluations are central in the pre-adoption phase and with Novak et al.

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(2022) that the technical complexity of blockchain can pose a substantial cognitive barrier for students without a computer-science background. The dominance of effort expectancy is one of the novel contributions of this study, suggesting that the relative weight of UTAUT predictors differs between students and practitioners according to their initial technology literacy. The magnitude of this effect is worth dwelling on. At 0.356, the effort expectancy path is roughly forty percent larger than the performance expectancy path (0.252) and more than double the social influence path (0.171), and its effect size of 0.259 is the only one in the model to reach the medium threshold. For a population that has not yet handled the technology, this ordering is telling: when the practical benefits of blockchain are still distant and largely imagined, the question that most concretely governs a student's willingness to begin learning is not whether the technology will eventually pay off but whether it can be learned at all. Perceived ease therefore functions less as a convenience factor and more as a gatekeeper to intention. This interpretation also carries a cautionary edge for educators. If ease of learning is the dominant lever, then curricula that introduce blockchain through its most technically demanding facets, such as cryptographic mechanics or smart-contract programming, risk depressing intention before interest can form, whereas an entry path organised around accounting-relevant use cases is more likely to keep the perceived learning curve within reach.

The support for H3 is consistent with the assertion of Venkatesh et al. (2012) that social influence remains relevant in voluntary contexts and with the collectivist and high power-distance character of the Indonesian academic environment (Hofstede, 1980), in which the views of lecturers, peers, and professional associations carry real weight. Nonetheless, among the supported paths, social influence has the smallest coefficient and effect size, and a post-hoc power analysis indicates that the statistical power for this path is relatively low (0.54); its significance should therefore be interpreted with caution.

The most striking finding is the rejection of H4. Facilitating conditions has a significant but negative effect on learning intention ($\beta = -0.243$). Because the construct is measured by two indicators with high loadings (FC1 = 0.957; FC3 = 0.882) and a high AVE (0.847), this negative direction is a statistically robust finding rather than a measurement artifact, and several theoretical explanations can be offered. First, within the UTAUT framework, facilitating conditions is theoretically positioned as a predictor of actual use behavior rather than intention (Venkatesh et al., 2003, 2012); when use behavior is not modeled, as in the present pre-adoption context, its role in shaping intention is theoretically ambiguous, and its effect is often weak or inconsistent. Second, the negative direction may reflect a sufficiency or motivational-substitution dynamic:

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students who perceive that institutional learning support is already well provided, namely quality materials and competent lecturers, may feel less urgency to invest personal effort in learning blockchain independently, because that need is seen as institutionally met, whereas students who perceive limited support may feel a greater need to learn on their own initiative as compensation. Third, the descriptive results reveal that facilitating conditions records the lowest mean and the widest variance, suggesting that blockchain learning support within the respondents' setting is uneven and that the construct reflects considerable variation in institutional readiness. Taken together, this negative finding should be interpreted cautiously and constitutes an important agenda for future research, both by modeling actual learning behavior and by conducting qualitative inquiry into the underlying mechanisms.

The descriptive profile of facilitating conditions lends weight to the substitution reading over the purely methodological one. Facilitating conditions is the only determinant whose mean falls into the moderate band (4.438), and it also records the widest dispersion among the antecedents (SD = 1.367), meaning that respondents are sharply divided in how well supported they feel. When this variation is set against the negative latent correlation with learning intention (−0.499), a coherent picture emerges: the students who report the strongest institutional provision are, on balance, not the ones who report the strongest intention to learn. Read through the sufficiency logic, well-resourced students may treat blockchain competence as something the institution will eventually deliver to them, so the perceived need for personal initiative recedes; conversely, students in less-provisioned settings may internalise the responsibility to learn independently precisely because they cannot rely on their institution to do it for them. If this mechanism is genuine, it carries an uncomfortable but useful policy implication, namely that expanding the supply of blockchain resources may not translate into greater willingness to learn unless it is paired with deliberate efforts to preserve student ownership of the learning process. The present cross-sectional design cannot adjudicate this mechanism directly, but it isolates a relationship specific enough to be tested in future work that models both provision and motivation explicitly.

Finally, the support for H5 validates the decision to extend UTAUT2 with technology awareness. This result corroborates the position of Parasuraman (2000) and Karahanna et al. (1999) that conceptual knowledge forms a legitimate basis for intention in the pre-adoption phase, and it echoes the qualitative evidence of Akter et al. (2024) identifying insufficient knowledge as a central barrier to blockchain adoption in accounting. Students with a higher level of knowledge of and exposure to blockchain

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possess a richer basis for evaluation and are therefore better able to form a substantive learning intention. With an effect comparable to that of performance expectancy, technology awareness proves to be a meaningful and theoretically relevant addition to the technology acceptance model in a student learning context.

Translating these results into guidance for accounting education in Indonesia requires attention to the ordering of the determinants rather than their presence alone. Because effort expectancy and performance expectancy dominate, the sequence in which blockchain is introduced matters as much as the decision to introduce it. A staged design is advisable, beginning with conceptual and accounting-contextual exposure, such as how distributed ledgers reshape the audit trail or how tokenised assets are recognised and measured, before any programming or cryptographic content is attempted. This sequence keeps the early perceived learning curve gentle, addressing the factor students weigh most heavily, while simultaneously making the professional payoff concrete, addressing the second strongest factor. Framing each module around a recognisable accounting problem, rather than around the technology in isolation, allows performance expectancy and effort expectancy to reinforce one another.

The significance of social influence, though modest, points to a complementary lever that costs little to activate. Departments can normalise blockchain learning by embedding it in the visible expectations of lecturers, by inviting practitioners and professional bodies such as the Institute of Indonesia Chartered Accountants to speak to its relevance, and by surfacing peer exemplars, since in a collectivist academic culture the observable choices of respected others carry persuasive weight. Technology awareness, which contributes an effect comparable to performance expectancy, argues for low-intensity but sustained exposure through seminars, guest lectures, and short awareness modules well before formal coursework begins, so that students reach the decision to learn already equipped with a frame of reference.

The negative role of facilitating conditions carries the most counterintuitive lesson for administrators. It suggests that procuring laboratories, software licences, and learning materials, while necessary, is not sufficient and may even prove self-defeating if it signals to students that mastery is the institution's responsibility rather than their own. Resource provision is therefore best coupled with mechanisms that protect and reward student initiative, such as project-based assessment, optional certification pathways, and recognition for self-directed exploration, so that support scaffolds motivation instead of substituting for it.

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CONCLUSION

This study examined the determinants of accounting students' intention to learn blockchain technology using a UTAUT2 model extended with technology awareness, based on data from 105 accounting students in Yogyakarta analyzed with PLS-SEM. The model explains 53.1% of the variance in learning intention and demonstrates tested out-of-sample predictive relevance. The evidence backs four of the five hypotheses: the intention to learn blockchain is positively and significantly shaped by performance expectancy, effort expectancy, social influence, and technology awareness, with effort expectancy proving the dominant predictor and technology awareness delivering an effect comparable to that of performance expectancy. In contrast, facilitating conditions has a significant but negative effect, so the corresponding hypothesis is not supported.

Theoretically, the study validates the application of UTAUT2 to a learning-intention context that is conceptually distinct from the intention to use, and shows that technology awareness enriches the model's explanatory power in an anticipatory adoption setting; the dominance of effort expectancy also contrasts with findings among practitioners, indicating that the relative weight of UTAUT predictors may differ across populations. Practically, because effort expectancy and performance expectancy are the strongest predictors, efforts to foster students' intention to learn blockchain should emphasize the clarity of career relevance and the design of materials that keep the learning curve manageable, supported by the encouragement of lecturers and the academic community and by campaigns that raise technology awareness. The negative effect of facilitating conditions offers an important lesson that the provision of institutional resources alone does not automatically increase learning intention and should be combined with strategies that nurture students' motivation and independent-learning initiative.

This study is subject to several limitations. Because it adopts a cross-sectional design and draws on a purposively selected sample of accounting students confined to Yogyakarta, its findings should be generalized with caution. The facilitating conditions construct is represented by only two indicators after two others were removed for failing convergent validity, and although social influence is significant, its statistical power is low. The study also measures intention rather than actual learning behavior, and the negative effect of facilitating conditions is not yet fully explained theoretically. Future research is encouraged to use larger and multi-region samples, to refine the measurement of facilitating conditions, to model actual learning behavior, and to combine quantitative and qualitative approaches, particularly to understand the negative effect of facilitating conditions and the dynamics through which learning intention is translated into action.

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Several of these directions merit more concrete specification. The negative effect of facilitating conditions is the finding most in need of follow-up, and it could be pursued in at least three complementary ways. A longitudinal design that tracks the same students from pre-adoption intention through to actual engagement with blockchain coursework would establish whether the inverse relationship persists once learning behaviour, rather than mere intention, becomes observable, and whether facilitating conditions reverts to its theorised positive role at that later stage. A multi-group analysis contrasting well-resourced and under-resourced institutions would test the substitution mechanism directly, since that account predicts a steeper negative slope precisely where institutional provision is strongest. Qualitative interviews would add the interpretive depth that a variance-based model cannot supply, letting students articulate in their own terms how they perceive the relationship between institutional support and personal responsibility for learning. Beyond facilitating conditions, the low statistical power observed for social influence indicates that a substantially larger and geographically broader sample is needed before its modest effect can be treated as settled, and such a sample would also permit moderation analyses, for example by prior exposure to financial technology or by field of specialisation, that the present sample size cannot reliably support. Extending the model to incorporate actual use behaviour, once blockchain becomes a routine part of accounting curricula, would finally allow the full UTAUT logic to be tested rather than its pre-adoption fragment alone.

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