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Unveiling the Blockchain Intention-Behavior Gap Among Young Developers

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ABSTRACT

This study assesses the factors influencing blockchain technology acceptance among young developers in Batam, Indonesia, with a specific focus on comparing two distinct behaviors: using blockchain-based applications and engaging in blockchain development. Data were collected through a survey of 215 young developers and analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM). The main outcomes reveal two fundamentally different adoption pathways. The intention to use blockchain applications is primarily driven by personal engagement and social influence, reflecting a "hype-driven" interest, and this intention strongly translates into actual usage behavior. Conversely, the model demonstrates a complete failure to explain development behavior, revealing a significant intention-behavior gap where the intention to develop shows no significant effect on actual development activities. The study concludes that for this demographic, hype-driven interest is sufficient for superficial application adoption but wholly inadequate for fostering development capabilities. Substantive adoption requires more than social trends; therefore, industry and educational focus should shift from promoting hype to enhancing technical literacy and demonstrating tangible use cases to bridge the gap from interest to competence.

I. Introduction

The evolution of blockchain technology is one of the most significant developments in the current digital ecosystem. Initially known through cryptocurrencies, blockchain has now evolved into a technological infrastructure adopted in various sectors such as finance, government, logistics, and education [1] [2] [3]. As the complexity of this technology increases, the role of software developers becomes increasingly crucial in ensuring its effective, secure, and sustainable implementation. However, the understanding and adoption rates of this technology among developers remain highly varied. In many developing countries, including Indonesia, much of the adoption still focuses on using blockchain-based applications such as crypto assets, rather than on in-depth system development [4] [5] [6]. Thus, it becomes crucial to identify the determining factors that shape the acceptance and application of blockchain technology within the developer community.

Previous research by [7] indicated a significant gap between knowledge and adoption of blockchain technology among software developers. The study highlighted a paradox where high interest and adoption intention among developers were not matched by deep technical understanding. This phenomenon creates an intention-behavior gap, showing that blockchain adoption at the developer level is not yet mature in terms of either understanding or application. The study emphasized the significant role of perceived usefulness and social influence in driving adoption intention, especially among young and novice developers.

Current literature confirms that the success of blockchain adoption heavily depends on the interplay of social, motivational, and technical factors. International studies consistently indicate that performance expectancy, trust, and technological awareness are primary drivers of adoption intention [2] [8] [9]. On the other hand, limited technological literacy and the perception of complexity often act as major barriers slowing down blockchain adoption in development practices [3] [10]. Other studies also highlight that personal innovativeness and personal engagement play a vital role in shaping the perceived usefulness of new technologies [11] [12]. Furthermore, several studies show that social influence strongly contributes to an individual's interest in blockchain, especially in highly connected digital societies influenced by tech trends [1] [13].

The urgency to analyse developer acceptance and usage of blockchain technology is increasing as its application expands across various industries [4] [8] [14]. A comprehensive understanding of the motivations, barriers, and perceptions among developers can significantly contribute to formulating more effective adoption strategies at both individual and organizational levels. Therefore, this study specifically explores how the interaction between perceived usefulness, personal engagement, and social influence shapes the intention and behavior of blockchain adoption within the developer community.

The conceptual framework of this study is an adaptation of the model proposed by [7], which assesses the adoption and utilization of blockchain technology among professional developers in two behavior contexts: application use and technology development. However, that research focused on the Eastern European context with highly experienced IT industry participants. A research gap emerges as there have been no studies testing this model in the context of a developing country like Indonesia, particularly among young developers with low blockchain literacy who are more influenced by social factors. This study aims to address this research gap by re-analyzing the [7] model in the Indonesian context to see to what extent the structural relationships among the constructs remain consistent in a different social and demographic environment.

To measure and analyze these acceptance determinants, this study applies a quantitative approach based on a modified version of the Technology Acceptance Model (TAM) [15]. The framework consists of several latent variables: Perceived Usefulness, Personal Engagement, Social Influence, Behavioral Intention, and Use Behavior. The analysis employs the Partial Least Squares–Structural Equation Modeling (PLS-SEM) method, which can simultaneously and deeply examine the relationships among these latent variables [4][14]. Consequently, this research is expected to provide an empirical contribution to enriching the technology acceptance model among developers and strengthening the theoretical foundation for future blockchain adoption studies.

Therefore, this study not only addresses a geographical and demographic research gap by testing the model in Indonesia's young developer context but also makes a crucial theoretical contribution by explicitly contrasting the adoption mechanisms for two distinct, yet interrelated, behaviors: passive application use versus active technology development. This comparative approach is essential for developing targeted strategies that can move developers from hype-driven interest to substantive technical capability.

II. METHOD

A. Technology Acceptance Model

This study adopts a modified Technology Acceptance Model (TAM) to evaluate the adoption of blockchain among software developers [7]. The model includes the following constructs:

- Perceived Usefulness (PU): Measures the extent to which blockchain technology is perceived to enhance efficiency, security, and transparency.
- Personal Engagement (PE): Measures personal motivation and interest in blockchain, including knowledge of regulations and the intention to learn.
- Social Influence (SI): Evaluates social and professional expectations, such as the fear of missing out and workplace demands.
- Behavioral Intention (BI) and Use Behavior (UB): Differentiated between using applications (apps) and using for development (dev).

All variables were operationalized using a Likert-type scale, in line with relevant validation approaches. The data collected from developers were subsequently processed using the Partial Least Squares–Structural Equation Modeling (PLS-SEM) method to evaluate the relationships among the latent variables.

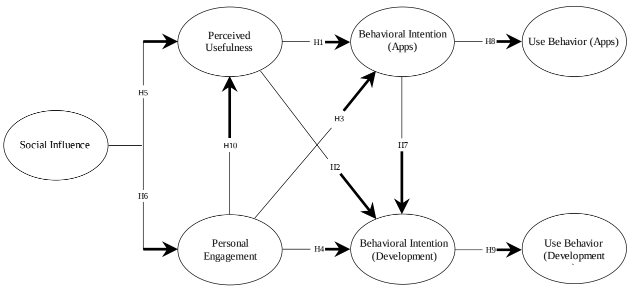

Figure 1. The conceptual framework for evaluating the adoption and use of blockchain by IT professionals, adapted from [7]

B. Research Hypotheses

All constructs were measured using indicators adapted from prior studies, with detailed operational definitions and corresponding survey items provided in Tables I to VII. Based on the adapted TAM, the hypotheses proposed in this study are as follows:

- H1: Perceived Usefulness is expected to positively affect intention to use blockchain-based applications.
- H2: Perceived Usefulness is expected to positively affect intention to use blockchain in development.
- H3: Personal Engagement is expected to positively affect intention to use blockchain-based applications.
- H4: Personal Engagement is expected to positively affect intention to use blockchain in development.

- H5: Social Influence is expected to positively affect Perceived Usefulness
- H6: Social Influence is expected to positively affect Personal Engagement.
- H7: Behavioral Intention to use blockchain-based applications is expected to positively affect behavioral intention to use blockchain in development.
- H8: Behavioral Intention to use blockchain-based applications is expected to positively affect actual usage of those applications.
- H9: Behavioral Intention to use blockchain for development is expected to positively affect actual usage of blockchain in development.
- H10: Personal Engagement is expected to positively affect Perceived Usefulness

These hypothesized relationships are visually represented in the research model shown in Figure 1.

TABLE I
OPERATIONAL DEFINITIONS VARIABLE PERCEIVED USEFULNESS (PU)

Variable	Code	Indicator
Perceived Usefulness (PU)	PU1	My perception is that data security will be strengthened and fraud will be minimized by using blockchain technology.
	PU2	For IT projects, I am convinced that adopting blockchain will provide significant financial benefits over time.
	PU3	My belief is that transactions within IT processes will become more transparent and verifiable with the use of blockchain.
	PU4	I am confident that the use of blockchain will result in a significant performance improvement for IT processes.

TABLE II
OPERATIONAL DEFINITIONS VARIABLE PERSONAL ENGAGEMENT (PE)

Variable	Code	Indicator
Personal Engagement (PE)	PE1	I have a good understanding of data protection rules concerning blockchain, including how regulations like GDPR apply to its applications
	PE2	The basic principles of blockchain technology are easy for me to grasp
	PE3	Out of genuine curiosity, I frequently discuss or read materials about blockchain during my leisure time

TABLE III
OPERATIONAL DEFINITIONS VARIABLE SOCIAL INFLUENCE (SI)

Variable	Code	Indicator
Social Influence (SI)	SI1	I am concerned that failing to adopt or understand blockchain could cause me to fall behind professionally in the IT community
	SI2	In my professional environment, I sense an increasing pressure to be well-versed in blockchain technology

TABLE IV
OPERATIONAL DEFINITIONS VARIABLE BEHAVIORAL INTENTION (APPS)

Variable	Code	Indicator
Behavioral Intention (Apps)	BIAPP1	It is my intention to utilize applications built on blockchain (e.g., cryptocurrencies, smart contracts) in the near future
	BIAPP2	I would be willing to integrate blockchain-based applications into my work for any suitable tasks.

TABLE V
OPERATIONAL DEFINITIONS VARIABLE BEHAVIORAL INTENTION (DEVELOPMENT)

Variable	Code	Indicator
Behavioral Intention (Dev)	BIDEV1	I plan to utilize blockchain technology for development purposes in the near future

TABLE VI
OPERATIONAL DEFINITIONS VARIABLE USE BEHAVIOR (APPS)

Variable	Code	Indicator
Use Behavior (Apps)	UBAPP1	What is your current frequency of using blockchain-based applications for your professional duties?

TABLE VII
OPERATIONAL DEFINITIONS VARIABLE USE BEHAVIOR (DEVELOPMENT)

Variable	Code	Indicator
Use Behavior (Development)	UBDEV1	What is your current frequency of using blockchain for any development-related work?

C. Research Context and Population Justification

This study specifically focuses on young developers in Batam, Indonesia, for several strategic reasons. Batam represents a developing digital economy within Indonesia's special economic zone, characterized by rapid technological adoption yet limited advanced technical expertise. The selection of young developers (aged 17-24) is particularly relevant as this demographic represents the future technology workforce in emerging digital economies, yet remains understudied in blockchain adoption literature. Their adoption patterns may differ significantly from experienced professionals due to differing levels of technical maturity, career establishment, and susceptibility to social influence. Furthermore, understanding blockchain adoption among this demographic provides crucial insights for designing effective educational interventions and industry strategies in similar developing regions.

III. Results and Discussion

A. Introduction

This section outlines the findings from the quantitative data analysis conducted to test the conceptual framework proposed in this study. The main objective is to present structured, data-based evidence obtained from a survey of 215 participants in the information technology developer community. The presentation begins with the demographic and professional profiles of the participants to provide context for the research sample. This is followed by descriptive statistics for each indicator to offer initial insights into their perceptions and intentions. The core focus is the evaluation of the measurement model (outer model) to ensure the validity and reliability of each latent variable, followed by the testing of the structural model (inner model) to verify the formulated research hypotheses. The entire data analysis process adopts the Partial Least Squares–Structural Equation Modeling (PLS-SEM) method.

B. Respondent Characteristics

The analysis of respondent characteristics provides a deep dive into the profile of the sample. Understanding the respondents' backgrounds, including age, familiarity with blockchain technology, and area of expertise, is a crucial foundation for accurately and comprehensively interpreting the research findings. A total of 215 respondents' data were analyzed in this study.

TABLE VIII
DISTRIBUTION OF RESPONDENTS BY AGE

Age	Frequency	Percentage (%)
17-24	209	97.21
25-34	5	2.33
35-44	1	0.47
Total	215	100.00

As presented in Table VIII, the demographic composition of this research sample is significantly dominated by the young age group. A total of 209 out of 215 respondents, or 97.21%, are within the 17 to 24 age range. The 25-34 age group accounts for only 2.33% of the total sample, while the 35-44 age group is represented by only one respondent (0.47%). This dominance of the young age group indicates that the research findings primarily reflect the views, perceptions, and intentions of novice developers, students, or early-career professionals. This becomes a key differentiator when compared to the main reference study, which targeted IT professionals with a majority age range of 25-44. This fundamental difference in experience and industry exposure has great potential to influence how respondents perceive and adopt new technologies like blockchain.

TABLE IX
RESPONDENTS' BLOCKCHAIN FAMILIARITY

Familiarity with the blockchain	Frequency	Percentage (%)
Never heard of it	45	20.93
Heard of it, but not familiar	120	5.81
Somewhat familiar	43	20.00
Very Familiar	7	3.26
Total	215	100.00

Table IX shows the respondents' level of understanding and familiarity with the concept of blockchain technology. The data reveals that the vast majority of respondents have a low level of familiarity. A total of 120 respondents (55.81%) stated they had "heard of it, but not familiar," and 45 respondents (20.93%) even stated they had "never heard of it at all." Combined, more than three-quarters of the sample (76.74%) have very limited or no knowledge at all regarding blockchain. Only a small fraction, 43 respondents (20.00%), felt "somewhat familiar," and only 7 respondents (3.26%) considered themselves "very familiar."

The combination of a very young age (Table VIII) and this low level of familiarity raise an important analytical consideration. There is a strong possibility that the respondents' perception of blockchain is shaped more by public discourse, social media trends, and technological "hype" than by practical experience or deep technical understanding. This phenomenon can create a "hype-driven perception" bias, where respondents' answers to constructs like Perceived Usefulness may not be based on a rational evaluation of the technology's capabilities, but rather on the repetition of popular sentiment. Consequently, the Social Influence construct is expected to play a highly dominant role in the model, not only in driving interest but also in shaping the basic perception of the technology's usefulness itself.

TABLE X
RESPONDENTS' AREAS OF EXPERTISE

Field of Expertise	Frequency	Percentage (%)
Other	70	32.56
Front-End Development	42	19.53

Data Science & Machine Learning	30	13.95
Database Administration	23	10.70
QA & Testing	20	9.30
Back-End Development	18	8.37
Full-Stack Development	10	4.65
DevOps	2	0.93
Total	215	100.00

Table X details the distribution of respondents based on their field of expertise in the information technology industry. The sample shows a wide range of professional diversity. The "Other" category is the largest, with 70 respondents (32.56%), which indicates the presence of various other roles outside the predefined categories. The most represented fields of expertise that follow are *Front-End Development* (19.53%), *Data Science & Machine Learning* (13.95%), and *Database Administration* (10.70%). Meanwhile, roles that are traditionally closer to core system implementation, such as *Back-End Development* (8.37%) and *Full-Stack Development* (4.65%), have a smaller representation. This diversity enriches the data, but it also confirms that the sample is not exclusively composed of core software developers but rather encompasses a broader spectrum of IT professionals.

C. Descriptive Statistics

To obtain an initial understanding of the responses for each survey item, a descriptive statistical analysis was performed. This process calculated key summary statistics, including the mean, median, and standard deviation, for all indicators corresponding to the model's constructs. Responses for each indicator were captured using a 5-point Likert scale, where 1 signified 'Strongly Disagree' and 5 represented 'Strongly Agree '.

TABLE XI
DESCRIPTIVE STATISTICS OF RESEARCH INDICATORS

Indicator	Mean	Median	Standard Deviation
PU1	4.112	4.000	0.782
PU2	3.930	4.000	0.835
PU3	3.972	4.000	0.829
PU4	4.042	4.000	0.837
PE1	3.693	4.000	0.934
PE2	3.605	3.000	0.898
PE3	3.302	3.000	1.160
SI1	3.828	4.000	0.927
SI2	3.865	4.000	0.913
BIAPP1	3.693	4.000	0.919
BIAPP2	3.791	4.000	0.872
BIDEV1	3.781	4.000	0.859
UBAPP1	3.642	4.000	0.919
UBDEV1	3.716	4.000	0.909

Table XI shows that, in general, respondents have a positive perceptual tendency towards blockchain technology. The mean values for most indicators measuring Perceived Usefulness (PU), Personal Engagement (PE), Social Influence (SI), and Behavioral Intention (BI) are above the neutral midpoint (3.0). For instance, the indicators for PU (PU1-PU4) have mean values ranging from 3.930 to 4.112, which indicates a general belief that blockchain is beneficial.

However, a very prominent and contradictory finding emerges from the Actual Use Behavior (Use Behavior) indicators. The indicators UBAPP1 (application usage) and UBDEV1 (development usage) show surprisingly high mean values, at 3.642 and 3.716, respectively. This finding is in stark contrast with the demographic data, which shows that 76.74% of respondents have very limited knowledge about blockchain (Table IX). Furthermore, this result is highly contrary to the reference study, where the median for actual usage behavior was reported as 1.0 (which means "Never").

The sharp gap between the low level of familiarity and the high reported usage level indicates a potential construct validity issue. It is highly likely that the respondents in this sample, who are mostly novices, interpreted the term "using" differently from what was intended by the research instrument or from the interpretation of a professional developer. "Using blockchain-based applications" may have been interpreted as ancillary activities such as owning a crypto wallet or reading about NFTs, rather than as the integration of the technology in professional tasks. Similarly, "use for development" could have been interpreted as merely trying online tutorials, not implementing them in a real project. This gap suggests that the results for the Use Behavior construct may reflect enthusiasm and engagement at a surface level rather than substantive use at a professional level, a critical nuance that must be considered in the interpretation of the structural model.

D. Measurement Model Analysis

Validation of the measurement model (outer model) is a fundamental step in the PLS-SEM methodology, which is essential to confirm that the research instrument has met the standards of validity and reliability. This process aims to verify that each indicator used accurately and reliably represents its intended latent variable. This assessment itself involves the evaluation of three main criteria: internal consistency reliability, convergent validity, and discriminant validity.

1) *Internal Consistency Reliability and Convergent Validity:* The quality of the measurement model was affirmed by evaluating two key criteria: internal consistency reliability and convergent validity. Internal consistency reliability was used to determine the interrelatedness of items within each construct, confirming that they measure a unified concept. Concurrently, convergent validity was assessed to ensure that each indicator correlated highly with other indicators of the same latent variable. This evaluation was performed using four primary metrics: Cronbach's Alpha, rho_A, Composite Reliability (rho_c), and Average Variance Extracted (AVE).

TABLE XII
RESULTS OF CONSTRUCT RELIABILITY AND CONVERGENT VALIDITY TEST

Construct	Cronbach's Alpha	rho_A	Composite Reliability (*rho_c*)	Average Variance Extracted (*AVE*)
Behavioral Intention (Apps)	0.797	0.797	0.908	0.831
Perceived Usefulness (PU)	0.884	0.886	0.920	0.741
Personal Engagement (PE)	0.840	0.843	0.903	0.757
Social Influence (SI)	0.819	0.824	0.917	0.846

The assessment of reliability and convergent validity, detailed in Table XII, confirms that all latent variables achieved the required standards. High internal consistency was demonstrated, as the Cronbach's Alpha and Composite Reliability values for every construct surpassed the 0.70 benchmark. Furthermore, strong convergent validity was established, with the Average Variance Extracted (AVE) for each latent variable exceeding the minimum 0.50 threshold. These high AVE scores signify that each construct accounts for more than half of the variance in its respective indicators, providing robust support for the model's convergent validity.

TABLE XIII
INDICATOR LOADINGS

	Loadings	T Statistics	P Values
BIAPP1 ← Behavioral Intention (Apps)	0.912	59.218	0.000
BIAPP2 ← Behavioral Intention (Apps)	0.911	63.372	0.000
BIDEV1 ← Behavioral Intention (Dev)	1.000	N/A	N/A
PE1 ← Personal Engagement (PE)	0.855	40.127	0.000
PE2 ← Personal Engagement (PE)	0.889	46.017	0.000
PE3 ← Personal Engagement (PE)	0.865	41.206	0.000
PU1 ← Perceived Usefulness (PU)	0.868	37.387	0.000
PU2 ← Perceived Usefulness (PU)	0.874	49.246	0.000
PU3 ← Perceived Usefulness (PU)	0.853	33.397	0.000
PU4 ← Perceived Usefulness (PU)	0.848	36.730	0.000
SI1 ← Social Influence (SI)	0.912	62.399	0.000
SI2 ← Social Influence (SI)	0.928	93.887	0.000
UBAPP1 ← Use Behavior (Apps)	1.000	N/A	N/A
UBDEV1 ← Use Behavior (Dev)	1.000	N/A	N/A

An examination of the indicator loadings, as detailed in Table XIII, further established the model's convergent validity. It was found that all indicators surpassed the standard benchmark of 0.708. The robustness of these loadings was underscored by their high T-statistics and significant p-values ($p < 0.001$), indicating that each indicator is a valid measure of its corresponding construct. Collectively, these results affirm that the measurement model possesses excellent reliability and strong convergent validity.

2) *Discriminant Validity:* Discriminant validity aims to confirm that each latent variable in the model is empirically distinct from the others. This ensures that each variable measures a unique phenomenon without significant conceptual overlap with other variables. The assessment for this criterion is conducted using the Heterotrait-Monotrait (HTMT) ratio.

The HTMT analysis in Table XIV reveals a crucial methodological finding. Most pairs of constructs show HTMT values below the conservative threshold of 0.90, which indicates adequate discriminant validity. However, there is one significant exception: the HTMT ratio between Social Influence (SI) and Behavioral Intention (Apps) (BIAPP) is 0.915, which exceeds this threshold.

This high HTMT value indicates that the two constructs are not statistically significantly different in the respondents' perceptions. In other words, for this research sample consists of young individuals with low familiarity with blockchain. Social pressure to engage with blockchain (SI) and their personal intention to use blockchain applications (BIAPP) are statistically almost indistinguishable. This finding provides strong basic evidence for the previously identified "hype-driven adoption" hypothesis. This implies that respondents' adoption intentions are not the result of an independent decision-making process, but rather a direct reflection of their adjustment to social trends and expectations. This is an important finding that underscores the powerful influence of external factors in shaping technological intentions among this demographic.

TABLE XIV
HETEROTRAIT-MONOTRAIT RATIO (HTMT)

	BI (*Apps*)	**BI (*Dev*)**	**PU**	**PE**	**SI**	**UB (*Apps*)**	**UB (*Dev*)**
BI (*Apps*)							
BI (*Dev*)	0.135						
PU	0.790	0.028					
PE	0.892	0.080	0.760				
SI	0.915	0.023	0.887	0.858			
UB (*Apps*)	0.834	0.083	0.597	0.785	0.742		
UB (*Dev*)	0.860	0.004	0.690	0.746	0.806	0.808	

3) *Collinearity Assessment:* Collinearity assessment is conducted to check for excessive multicollinearity among the indicators in the model. High multicollinearity can interfere with the model's estimation and reduce the reliability of the results. This assessment is performed by examining the Variance Inflation Factor (VIF) values.

TABLE XV
VARIANCE INFLATION FACTOR (VIF)

Indicator	**VIF**
BIAPP1	1.781
BIAPP2	1.781
PE1	1.807
PE2	2.141
PE3	2.077
PU1	2.484
PU2	2.485
PU3	2.321
PU4	2.097
SI1	1.924
SI2	1.924

As shown in Table XV, the VIF values for all indicators are well below the commonly used threshold of 5.0, and even below the more conservative threshold of 3.0. This result confirms that there are no serious multicollinearity issues among the indicators at the measurement model level. This provides confidence that the parameter estimates in the structural model will not be distorted by excessive correlation among predictors.

E. Structural Model Analysis and Hypothesis Testing

Once the measurement model's validity is confirmed, the analysis proceeds to the structural model (inner model). This stage focuses on testing the hypothesized causal relationships between the constructs. This involves evaluating the model's explanatory power (R^2), analyzing the path coefficients to test the hypotheses, and assessing its predictive relevance (Q^2).

1) *Model Explanation (R-Square):* The explanatory power of the structural model is assessed using the coefficient of determination (R^2). This metric quantifies the proportion of variance in a dependent (endogenous) construct that is accounted for by its influencing predictor (exogenous) constructs.

TABLE XVI
COEFFICIENT OF DETERMINATION (R-SQUARE) VALUE

	R^2	**P Values**
Perceived Usefulness (PU)	0.606	0.000
Personal Engagement (PE)	0.511	0.000
Behavioral Intention (Apps)	0.592	0.000
Use Behavior (Apps)	0.554	0.000
Behavioral Intention (Development)	0.025	0.132
Use Behavior (Development)	0.000	0.499

The R-Square values presented in Table XVI offer a dual narrative regarding the model's explanatory capacity, highlighting both its strengths and its fundamental limitations in predicting final behavior. On one hand, the model effectively clarifies the antecedents of application use intention. Specifically, it accounts for a substantial portion of the variance for Perceived Usefulness (PU) at 60.6%, Personal Engagement (PE) at 51.1%, and Behavioral Intention (Apps) at 59.2%.

However, on the other hand, the model demonstrates a total failure in explaining development behavior. The *R*-Square value for Use Behavior (Development) is 0.000, which literally means that all the factors in this model cannot at all explain why a respondent ultimately engages in development with blockchain. The very low *R*-Square value for Behavioral Intention (Development) (2.5%) also reinforces this finding.

This divergence is a central finding, indicating that the adapted conceptual framework is inadequate for explaining the transition from intention to actual action. Although the model can map some of the initial triggers for intention on the application side, its total failure in explaining development behavior shows that the driving factors for engaging in complex software engineering tasks are outside the scope of the model.

2) *Hypothesis Testing (Path Coefficients):* Hypothesis testing is conducted by analyzing the path coefficients and their significance values (p-values). The path coefficient (β) indicates the strength and direction of the relationship between constructs. A T-Statistics value greater than 1.96 and a P-Value less than 0.05 indicate that the relationship is statistically significant.

TABLE XVII
HYPOTHESIS TESTING RESULTS (PATH COEFFICIENTS)

		Path coefficient (*β*)	**T Statistics**	**P Values**
H1	PU → BI (Apps)	0.327	5.195	0.000
H2	PU → BI (Dev)	-0.146	1.455	0.073
H3	PE → BI (Apps)	0.513	8.661	0.000
H4	PE → BI (Dev)	0.026	0.240	0.405
H5	SI → PU	0.585	8.925	0.000
H6	SI → PE	0.715	18.811	0.000
H7	BI (Apps) → BI (Dev)	0.199	2.057	0.020
H8	BI (Apps) → UB (Apps)	0.744	17.573	0.000
H9	BI (Dev) → UB (Dev)	0.004	0.062	0.475
H10	PE → PU	0.244	3.661	0.000

The analysis in Table XVII presents the hypothesis testing, which reveals an adoption dynamic that is split into two fundamentally different pathways. Each relationship is analyzed based on three main metrics: the Path Coefficient (*β*), which indicates the strength and direction of the influence; the T-Statistics, which measure the significance of the coefficient; and the P-Values, which serve as the basis for statistical decisions. The main finding from this testing is the model's success in mapping the application adoption pathway, which contrasts with its revealed failure in the development adoption pathway. This failure is specifically identified through three rejected hypotheses (H2, H4, and H9), which collectively highlight a fundamental intention-behavior gap in the context of development. The following is a detailed analysis of each hypothesis based on the data in Table XVII:

- H1: Perceived Usefulness (PU) → Behavioral Intention (Apps). This hypothesis is accepted. The analysis showed a path coefficient (β) of 0.327, signifying a substantial positive effect. A robust T-Statistic of 5.195, coupled with a p-value of 0.000, affirms the high statistical significance of this relationship. This result indicates that a stronger belief in the benefits of blockchain technology directly corresponds with a higher intention to use its applications.
- H2: Perceived Usefulness (PU) → Behavioral Intention (Dev). This hypothesis is rejected. The relationship failed to achieve statistical significance (P-Value = 0.073; T-Statistics = 1.455). Although the path coefficient shows a negative direction (β = -0.146), the low significance indicates that there is insufficient statistical evidence to conclude an influence of PU on development intention in this sample. This implies that for novice developers, a belief in the technology's benefits alone is not enough to form an intention to engage in development.
- H3: Personal Engagement (PE) → Behavioral Intention (Apps). This hypothesis is accepted. The analysis revealed a path coefficient (β) of 0.513, signifying a very strong positive influence. The statistical significance of this relationship was confirmed by an exceptionally high T-Statistic of 8.661 and a p-value of 0.000. This finding establishes that an individual's personal interest and engagement are powerful predictors of their intention to use applications based on blockchain technology.
- H4: Personal Engagement (PE) → Behavioral Intention (Dev). This hypothesis is rejected. The results show a very weak influence (β = 0.026) and are not statistically significant, with a P-Value of 0.405 and a T-Statistics of only 0.240. This finding implies that personal interest alone is not sufficient to drive the intention to engage in development.
- H5: Social Influence (SI) → Perceived Usefulness (PU). This hypothesis is accepted. The relationship is proven to be very strong and significant (β = 0.585; T-Statistics = 8.925; p = 0.000). This finding underscores that respondents' perception of blockchain's usefulness is highly influenced by trends and expectations in their social environment.
- H6: Social Influence (SI) → Personal Engagement (PE). This hypothesis is accepted and represents the strongest relationship in the model. With a path coefficient (β) of 0.715 and an exceptionally high T-Statistics value (18.811), it is evident that social influence is the primary trigger driving respondents' personal interest in blockchain.
- H7: Behavioral Intention (Apps) → Behavioral Intention (Dev). This hypothesis is accepted. With a T-Statistics value (2.057) exceeding 1.96 and a significant P-Value (0.020). The path coefficient (β = 0.199) indicates a positive influence from the intention to use applications on the intention to develop. This result points to a potential transition effect, where initial users may evolve into prospective developers.
- H8: Behavioral Intention (Apps) → Use Behavior (Apps). This hypothesis is accepted. A very strong path coefficient (β = 0.744) and a massive T-Statistics value (17.573) confirm that the intention to use applications

is effectively translated into actual usage behavior (p = 0.000).

- H9: Behavioral Intention (Dev) → Use Behavior (Dev). This hypothesis is rejected. With a path coefficient close to zero (β = 0.004) and a P-Value of 0.475, this relationship is not significant at all. This is a crucial finding that identifies a significant intention-behavior gap, where the intention to develop does not carry through to actual action.
- H10: Personal Engagement (PE) → Perceived Usefulness (PU). This hypothesis is accepted. There is a positive and significant influence (β = 0.244; T-Statistics = 3.661; p = 0.000). This indicates that the higher an individual's personal engagement with blockchain, the more they perceive it as a useful technology.

3) *Predictive Relevance (Q²_predict):* Predictive relevance, measured by Q²_predict, assesses the model's ability to predict the indicator values of new (out-of-sample) data. A Q²_predict value greater than zero indicates that the model has predictive relevance.

TABLE XVIII
PREDICTIVE RELEVANCE MODEL (Q²_PREDICT)

Indicator	Q²_ predict	PLS-SEM_ RMSE	PLS-SEM_ MAE	LM_ RMSE
PU4	0.505	0.591	0.475	0.585
BIAPP2	0.454	0.648	0.493	0.647
PU2	0.420	0.639	0.480	0.641
PE2	0.420	0.686	0.519	0.691
BIAPP1	0.418	0.704	0.524	0.706
PE1	0.404	0.724	0.544	0.723
UBAPP1	0.401	0.714	0.556	0.694
PU3	0.391	0.650	0.503	0.658
PU1	0.355	0.631	0.501	0.635
PE3	0.313	0.966	0.764	0.971
UBDEV1	0.001	0.913	0.773	0.631
BIDEV1	-0.004	0.865	0.730	0.870

The Q²_predict results in Table XVIII fully support the findings from the R^2 and path coefficient analyses. The model demonstrates moderate to high predictive relevance for all indicators related to the "application" side of the model (PU, PE, BIAPP, UBAPP). All Q²_predict values for these indicators are positive, which confirms the model's ability to perform out-of-sample predictions.

Conversely, the predictive relevance for the "development" side is extremely poor. The UBDEV1 indicator has a Q²_predict value approaching zero (0.001), indicating almost no predictive power. More significantly, the BIDEV1 indicator has a negative Q²_predict value (-0.004). This negative value is a strong statistical confirmation that, for predicting development intention, the model performs worse than simply using the mean value. This definitely validates the model's failure to explain or predict blockchain adoption for development purposes in this sample.

4) *Model Fit Assessment (SRMR):* To ensure the robustness of the measurement model, this study evaluated the approximate model fit using the Standardized Root Mean Square Residual (SRMR). The SRMR serves as a measure of the discrepancy between the observed correlation matrix and the model-implied correlation matrix. As presented in Table XIX, the analysis of the saturated model yields an SRMR value of 0.061. This result falls well below the generally accepted threshold of 0.08, confirming that the model demonstrates a good fit and that the empirical data are accurately represented by the proposed measurement structure.

TABLE XIX
MODEL FIT ASSESSMENT (SRMR)

	Original Sample (O)	Sample Mean (M)	95%	99%
Saturated Model	0.061	0.035	0.041	0.046
Estimated Model	0.228	0.049	0.063	0.072

5) *Goodness of Fit (GoF):* In addition to SRMR, the Goodness of Fit (GoF) index was calculated manually to validate the overall predictive performance of the model. The GoF is determined by calculating the geometric mean of the average variance extracted (AVE) and the average coefficient of determination (R^2). Based on the calculation using the average AVE of 0.794 (derived from Table XII) and the average R^2 of 0.381 (derived from Table XVI), the resulting GoF value is 0.550. Since this value exceeds the standard baseline of 0.36 for large effect sizes, it can be concluded that the global model possesses substantial predictive power, effectively balancing the measurement and structural components.

F. Discussion

The analysis of this study reveals the dynamics of blockchain adoption, which is divided into two fundamentally different paths. Its main findings not only confirm but also expand on the insights of previous studies, particularly in the context of the demographics of young developers in Batam.

In terms of application usage, Social Influence (SI) emerged as the dominant trigger that significantly drove Personal Engagement (PE) (β = 0.715) and Perceived Usefulness (PU) (β = 0.585). These findings are consistent with the study by [7], which also identified social influence as a significant factor in shaping adoption intentions. However, this study reveals fundamental differences in the mechanisms of influence.

Unlike studies in more mature domains, such as financial applications that emphasize information security and technology awareness [13], or digital payment systems that focus on trust [9], adoption among our sample of young developers appears to be driven more by trends and social pressure. This is reflected in the HTMT value of 0.915 between SI and Behavioral Intention (Apps), which indicates that these two constructs are statistically almost indistinguishable in the respondents' perceptions.

Furthermore, the intention formed from this social influence was successfully translated into actual usage behavior, as evidenced by the acceptance of hypothesis H8 ($\beta = 0.744$). However, these findings should be interpreted with caution. Considering that 76.74% of respondents had a very low level of familiarity with blockchain, the reported usage behavior is likely to be superficial. This interpretation is consistent with the research by [4], which found that interest in blockchain in Batam is often not accompanied by a deep technical understanding.

The most crucial finding of this study is the total failure of the development path, which indicates a very significant intention-behavior gap. Hypothesis H9 (BI Dev → UB Dev) was firmly rejected ($\beta = 0.004$) and the model constructed had zero explanatory power ($R^2 = 0.000$) for the development behavior variable.

These findings contrast sharply with the reference study by [7]. Although their research also found a gap between intentions and development behavior, our results show a complete disconnect. This drastic difference is most likely due to fundamental demographic differences. Our sample was dominated by young and novice developers (97.21% aged 17-24), while [7] targeted experienced IT professionals (the majority aged 25-44).

As indicated by the rejection of hypotheses H2 (PU → BI Dev) and H4 (PE → BI Dev), neither Perceived Usefulness nor Personal Engagement alone is sufficient to form sustainable development intentions. This finding supports the research of [16], which emphasizes the importance of a readiness model for blockchain adoption in the software development sector. In line with this, [17] identified specific constructs such as technical feasibility and developer skills that are not covered by the general Technology Acceptance Model (TAM).

Theoretically, this study confirms that the effectiveness of the TAM model is highly dependent on the demographic context and the complexity of the behavior being measured. This model, although proven effective in explaining low-cost use intentions, is inadequate for explaining high-barrier behaviors such as software development. The failure of the model ($R^2 = 0.000$ for Use Behavior Development) is a strong signal that factors outside this model, such as technical literacy, developer readiness [16], and contextualized software engineering challenges [18], are the real determinants.

These findings are consistent with the research by [10], which integrates Innovation Diffusion Theory with TAM to understand blockchain adoption in developing markets, as well as the study by [8], which identifies organizational and technical factors as critical determinants in blockchain adoption.

In practical terms, the implications of this research are clear to young developers in Batam. Strategies that rely solely on hype risk producing only superficial users. As suggested by [16], in order to bridge the significant intention-behavior gap and foster a competent developer workforce, the focus of industry and education needs to shift. This shift must be made from simply promoting trends to concrete efforts such as improving in-depth technical literacy, demonstrating real and applicable use cases, and building a comprehensive and sustainable ‘readiness’ ecosystem.

G. Theoretical Contributions

This study provides several significant theoretical contributions to the technology acceptance literature, particularly in the context of emerging technologies and developer communities in developing countries.

Extension of TAM Boundaries: This research extends the theoretical boundaries of the Technology Acceptance Model by demonstrating its contextual limitations in explaining complex technological behaviors. While TAM effectively explained blockchain application adoption among young developers ($R^2 = 59.2\%$ for Behavioral Intention-Apps), it completely failed to explain development behavior ($R^2 = 0.000\%$ for Use Behavior-Development). This empirical evidence reveals that TAM, while robust for predicting low-barrier consumption behaviors, is inadequate for explaining high-barrier productive behaviors requiring substantial technical competence and commitment.

Hype-Driven Adoption Concept: The study introduces and empirically validates the concept of "hype-driven adoption" as a distinct adoption mechanism among young technology enthusiasts. The exceptionally high HTMT ratio between Social Influence and Behavioral Intention-Apps (0.915) indicates these constructs are statistically indistinguishable in our sample, suggesting adoption intention is essentially synonymous with social influence rather than resulting from independent decision-making processes.

Intention-Behavior Gap Understanding: This research provides nuanced understanding of the intention-behavior gap in technology adoption. While previous research noted this gap, our findings reveal a complete disconnect specific to development activities ($\beta = 0.004$, $p = 0.475$), suggesting the intention-behavior relationship may be nonexistent for complex technological behaviors when foundational competencies are lacking.

Contextual Boundary Conditions: The study demonstrates how social influence mechanisms operate differently across demographic contexts. While previous research found social influence to be a significant but distinct factor among experienced professionals, our study shows it becomes the dominant, almost exclusive driver among novice developers, highlighting demographic variables as crucial boundary conditions in technology acceptance theories.

Methodological Contribution: The application of PLS-SEM with comprehensive model evaluation metrics (including HTMT, R^2, Q²_predict, and path coefficients) provides a methodological framework for future technology adoption studies in similar contexts, particularly for research examining both simple and complex technological behaviors within the same model.

H. Limitations and Future Research

While this study provides valuable insights into blockchain adoption patterns among young developers, several limitations should be acknowledged to properly contextualize the findings and guide future research endeavors.

The geographical limitation to Batam, Indonesia, affects the generalizability of our results. Although Batam represents an emerging digital economy in Indonesia, its specific socio-economic context may not fully represent other regions in Indonesia or other developing countries. Future research should replicate this study in different geographical contexts, including other Indonesian cities and other developing nations, to enhance the external validity of the findings and identify potential regional variations in blockchain adoption patterns.

The measurement of Use Behavior constructs may have been subject to interpretation bias, as evidenced by the surprisingly high self-reported usage behavior despite low blockchain familiarity among respondents. This suggests participants might have interpreted "using blockchain" differently than intended, potentially including peripheral activities rather than professional implementation. Future studies should employ more precise behavioral measures, incorporating actual usage metrics, log data, or mixed-methods approaches to triangulate behavioral data and enhance measurement validity.

The adapted TAM framework demonstrated complete failure to explain development behavior ($R^2 = 0.000$), indicating significant omitted variables critical for understanding complex technological behaviors. Future research should integrate additional constructs from complementary theoretical frameworks, including technical competence, programming self-efficacy, learning resources accessibility, and mathematical foundations, to develop a more comprehensive model capable of explaining blockchain development adoption.

The cross-sectional design of this study limits our ability to make causal inferences and understand the evolution of adoption patterns over time. Future research should employ longitudinal designs to track how developers' perceptions, intentions, and behaviors change as they gain experience and technical competence, particularly examining the critical transition from application use to development activities and identifying potential tipping points in this progression.

The demographic composition of our sample, predominantly consisting of young developers (97.21% aged 17-24), limits our understanding of how professional experience moderates adoption patterns. Future studies should include more experienced developers across different career stages to examine how industry exposure, technical maturity, and professional specialization influence blockchain adoption pathways, potentially revealing different adoption mechanisms across experience levels.

These limitations, while constraining the current study's generalizability, provide fruitful directions for future research to build upon these findings and develop more nuanced understanding of blockchain technology adoption in software development contexts across different demographic and geographical settings.

I. Practical Implications

Based on the research findings regarding the gap between interest and actual blockchain development behavior, this study provides practical implications for various stakeholders in the technology ecosystem.

For educational institutions and training providers, it is necessary to develop specialized modules focusing on smart contract programming and decentralized application development. The curriculum should be designed with a project-based learning approach that integrates real case studies to bridge the competence gap identified in this research. Learning should be structured progressively from basic blockchain concepts to advanced development skills.

For industry and technology companies, a strategic shift from merely building hype to substantively developing technical competencies is required. Companies can provide sandbox environments for development experiments, compile comprehensive technical documentation, and create mentorship programs connecting novice developers with experienced ones. The industry also needs to establish clear career paths and certifications for blockchain developers.

For policymakers and local government, it is recommended to support the development of blockchain innovation centers in Batam's special economic zone. Funding allocation for technical training programs and workshops for young developers is needed to build local blockchain talent. Strategic partnerships between educational institutions and industry should be facilitated to ensure curriculum relevance to market needs.

For blockchain communities and advocacy groups, a reorientation of discussions from price speculation to technical education and use case development is necessary. Organizing hackathons and coding competitions focused on solving local problems using blockchain technology can encourage more substantive adoption. The development of educational content in Indonesian is also required to enhance the accessibility of blockchain concepts for young developers.

These practical implications directly address the core research finding that social influence and hype-driven interest are insufficient for developing genuine blockchain development capabilities. By implementing these recommendations, stakeholders can systematically bridge the intention-behavior gap and transform superficial interest into substantive technical competence, ultimately supporting the growth of Indonesia's blockchain ecosystem.

IV. CONCLUSION

By adapting the Technology Acceptance Model (TAM) framework, this study investigated the determinants behind the adoption of blockchain technology among the young developer demographic in Batam. Findings from the Partial Least Squares–Structural Equation Modeling (PLS-SEM) analysis indicate a fundamental dualism in the adoption dynamics, which is divided into a pathway for application utilization and a pathway for development activity.

The intention to use blockchain applications among young developers is proven to be strongly influenced by Personal Engagement, which in turn is heavily driven by Social Influence. This "hype-driven adoption" phenomenon is effectively translated into actual usage behavior, where intention is shown to have a highly significant influence on the act of using applications. Nevertheless, considering the respondents' low level of familiarity with the technology, this behavior is interpreted as surface-level adoption.

Conversely, the decision to engage in blockchain development reveals a more rational yet inhibited pattern. The most crucial finding of this research is the significant intention-behavior gap on the development path. The intention to develop, although formed, is ultimately not strong enough to be realized into actual development behavior, as the relationship between the two proved to be insignificant.

Theoretically, this research confirms that the effectiveness of the TAM model is highly dependent on the demographic context and the complexity of the behavior being measured. Among a young audience, enthusiasm driven by social trends is sufficient to encourage low-cost adoption (trying applications), but not for actions that demand high commitment and competence (development). Practically, this finding provides a critical implication: to bridge the gap from interest to tangible development capability, the industry's focus must be shifted from merely building hype towards enhancing technical literacy, demonstrating clear use cases, and providing adequate educational resources.

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