RESEARCH PAPER

The Convergence of AI, Blockchain, and Large Engineering Projects: Enhancing Financial Literacy through Technological Engagement

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ABSTRACT

The emergence of AI, blockchain, and large projects leads to the appearance of a new environment where one can develop financial literacy; nevertheless, technological adoption and financial competence have mainly been considered separately. This paper focuses on the relationship between AI engagement, blockchain engagement, technological engagement, and financial literacy under the moderating role of Project Context. Based on a cross-sectional survey conducted among 412 participants involved in infrastructure, energy, and PPP projects, the study uses the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology and employs Partial Least Squares Structural Equation Modeling with 5,000 bootstrap samples. As follows from the analysis, AI engagement has more impact on technological engagement ($\beta = 0.412$) compared to blockchain engagement ($\beta = 0.287$); moreover, technological engagement positively affects financial literacy ($\beta = 0.486$), while project context acts as a moderator in this relationship ($\beta = 0.148$, $p = 0.004$). Within the structural model, 41.1% variance in technological engagement and 38.9% variance in financial literacy are explained. This allows placing technological engagement in a completely new light and viewing it not only as a result but also as a product of using technologies.

Keywords: *Artificial intelligence; Blockchain; Financial literacy; Technological engagement; Large engineering projects*

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HIGHLIGHTS

- Integrates AI, blockchain, and engineering projects to increase financial literacy through engagement.
- Builds a TAM–UTAUT framework tested with 412 stakeholders from large engineering projects.
- AI engagement ($\beta = 0.412$) influences technological engagement more than blockchain ($\beta = 0.287$).
- Technological engagement is a strong predictor of increased financial literacy ($\beta = 0.486$), which is context-driven.
- Reframes technological engagement as the driver of financial capabilities development.

ABBREVIATIONS

AI	Artificial Intelligence	**FL**	Financial Literacy
AIE	AI Engagement	**HTMT**	Heterotrait–Monotrait Ratio
AVE	Average Variance Extracted	**PC**	Project Context
BCE	Blockchain Engagement	**PLS-SEM**	Partial Least Squares Structural Equation Modeling
BCT	Blockchain Technology	**PPP**	Public–Private Partnership
BOT	Build–Operate–Transfer	**SEM**	Structural Equation Modeling
CI	Confidence Interval	**TAM**	Technology Acceptance Model
CMB	Common Method Bias	**TE**	Technological Engagement
CR	Composite Reliability	**UTAUT**	Unified Theory of Acceptance and Use of Technology
		VIF	Variance Inflation Factor

NOMENCLATURE

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Latin symbols		***Greek symbols***	
$C_{k,i}$	control variable k for observation i	α	Cronbach's alpha
f^2	Cohen's effect size	β	standardized path coefficient
N	total sample size	γ	exogenous-to-endogenous coefficient
n	sample subset size	δ	measurement error term
p	probability value (two-tailed)	ε	regression residual
Q^2	Stone–Geisser predictive relevance	ζ	structural disturbance (SEM)
R^2	coefficient of determination	η	endogenous latent variable
SE	bootstrapped standard error	λ	outer loading
t	bootstrap t-statistic	ξ	exogenous latent variable
VIF	variance inflation factor	ρ_A	consistent reliability coefficient
x_i	observed indicator i	ρ_C	composite reliability

Subscripts			
i	observation index (i = 1, …, N)	k	control variable index
j	endogenous construct index	LL	lower limit of 95% CI
		UL	upper limit of 95% CI

1. INTRODUCTION

The coming together of technology and finance has brought about changes in how people, businesses, and governments interact with economic decision-making processes, while, at the same time, the world is experiencing inequalities regarding the level of financial literacy among different communities. According to recent findings of the Global Findex Database, even though the use of digital payments has significantly increased following the onset of the COVID-19 pandemic, a vast percentage of the world's population continues to have trouble comprehending basic concepts of finance, as well as using the services effectively [1]. The problem brings about an important policy issue since, in addition to being an individual quality, financial literacy is a valuable asset for people because it affects savings, investments, borrowing, and retirement plans [2]. Empirical evidence accumulated across diverse populations further demonstrates the strong link between financial literacy and financial behavior with clear implications on different levels [3, 4].

In this case, there are two main technological developments that have been at the forefront in facilitating change in the financial environment. AI has shifted its role from that of an analysis tool to one that is essential in facilitating predictive finance, decision making, and personal advisory, whereas blockchain has changed from an essential technology behind cryptocurrencies to being a decentralized architecture that can transform transactions, trust, and contracts [5]. In previous studies, there are references to how quickly these two technologies have been adopted in construction project life cycles [6] and in general AEC industry settings, whereby blockchain technology is already being applied in contract management, payments, dispute resolution, and coordination among other aspects [7]. At the same time, research in financial services has examined how the complementary nature that arises from adopting the technologies can be used for security, auditing, and regulatory purposes [8, 9]. However, studies that adopt a behavioral lens in analyzing both AI and blockchain are quite rare, while theoretical analyses usually precede empirical work.

The wide application of engineering projects offers a unique opportunity for examining the connection between financial literacy and project success. Any engineering project involves complicated financing, coalitions, and vulnerability to cost overrun. Recent researches have proven that the distribution of cost overruns follows the rule of power law rather than the normal distribution [10]. It means that there exists a systemic risk of dealing with extreme cases when costs become too high to be managed using the common techniques of forecast modeling. Moreover, the framework of the PPP agreement, frequently used when implementing engineering projects, causes additional problems for all the parties involved [11], since it contributes to information asymmetry and makes the contractual obligation of each party questionable. In such conditions, financial literacy becomes an important determinant of project success. However, existing research has focused mainly on analyzing technology and financial literacy as separate phenomena. Although studies on FinTech market development recognize the necessity of adequate financial literacy as one of the prerequisites for technology usage [12], they rarely discuss the impact of consistent interaction with AI- and blockchain-based systems on acquiring financial literacy. Consumer behavior analysis also reveals the significant distance between merely having access to technology and learning new things through consistent usage [13], supporting recommendations for a more integrated approach to the issue [14].

In order to fill such gaps, the current study investigates how the intersection between artificial intelligence, blockchain technology, and large-scale engineering projects increases financial literacy via technological engagement, as technology-based engagement is seen both as an effect of technology integration and an instrument for improving financial literacy. This paper makes three contributions. It provides a conceptual framework that connects the areas of finance, project management, and technology integration that have not been connected before. Large engineering projects are also considered as sites of situated learning where technological engagement can result in financial literacy rather than just being used for it. The empirical findings further provide valuable insights to policymakers, project sponsors, financial educators, and technology providers who aim at matching innovations with capability development.

2. ANALYSIS OF THE PROBLEMS

2.1 AI and Blockchain in Engineering Finance

Engineering projects exist in financial environments where many-party transactions, late payments, and significant transaction costs are present. All these aspects present a basis for blockchain application due to its unique features. Based on evidence from systematic research conducted from a transaction cost perspective, it has been established that the use of blockchain technology in construction project management minimizes transaction costs; however, its efficiency depends on the project size and nature [15]. In line with this, decentralized bidding processes based on the implementation of smart contracts can be used to minimize opaqueness and discretion during the bidding process [16]. Related literature on construction cost management provides further evidence that integrating blockchain technology and cryptography results in better traceability of financial data, hence minimizing informational asymmetries in the industry [17].

Artificial intelligence has an effect on the previously described situation due to the opportunities provided by predictions compared to infrastructure. In particular, machine learning models, such as gradient boosting approaches, have shown better results than regression approaches in predicting cost overruns, offering investors and sponsors early warnings [18]. In conjunction with blockchain technology, this approach becomes a reinforcing circle because artificial intelligence increases the accuracy of the decisions made, while blockchain guarantees the security of the information used and the transactions made [19]. Nevertheless, studies that have been done on the issue tend to be separated by disciplines, where the technological efficiency of the process can be viewed from the perspective of management but may also be employed as a financial tool.

2.2 Financial Literacy: Concepts and Measurement

The concept of financial literacy can be defined as an individual's capacity to comprehend financial information and make decisions related to savings, borrowing, investments, and managing risks. According to meta-analyzes of numerous randomized programs, it was proven that financial literacy training could lead to significant improvements not only in knowledge about finances but also in behavior associated with such activities as budgeting, debt management, and planning for retirement [20]. It should be noted that financial literacy tends to be relatively stable throughout the life course and has predictive value, thus being regarded as a kind of human capital [21].

On the measure, this research area has traditionally used the Big Three and Big Five scales, which assess an individual's knowledge regarding compound interest, inflation, and diversification. Recent systematic literature review delineates an ever-widening list of determinants and demonstrates the growing diversity in methodological approaches in the area [22]. The digitalization of finance services has led scholars to postulate that traditional measures inadequately account for the capabilities necessary in algorithmic decision-making settings, thus calling for a rethinking of the conceptual framework and the inclusion of digital trust, algorithmic literacy, and cyber-risk knowledge [23].

2.3 Technological Engagement as a Bridge

Engagement in technology refers to the continuous and deliberate interaction of the individual with technological financial instruments not only from the perspective of use but also through frequency and intensity. From research evidence, it is seen that digital financial literacy is a mediator through which technological engagement positively affects the state of financial well-being [24]. The current literature shows that based on the theory of UTAUT, FinTech usage by students of universities is influenced by the performance expectation and facilitating conditions of the user, implying the role of the environment in influencing the behavior of the use [25]. Moreover, further studies conducted in the field of finance show the impact of digitalization on the process of service delivery and cognition of the user [26].

The UTAUT2 models, where constructs concerning trust theories were added, show that platform reliability-based trust plays an important role in the extent of users' deep engagement [27], while other research connected to behavioral intention theories pays attention to social influence and habit formation [28]. Other research work done in the realm of emerging markets reveals gender differences in usage, thus implying that engagement is situational [29]. Other research work done in the realm of emerging markets reveals gender differences in usage, thus implying that engagement is situational [30]. Nevertheless, no theory explains how engagement can contribute to building users' financial skills.

2.4 Research Gaps and Problem Statement

In summary, the above review brings into focus three related weaknesses in the existing literature. The opening weakness relates to the compartmentalization of studies about AI and blockchain and the failure to analyze the performance merits of the technologies in conjunction with the behavior they induce in the engineering-finance context. A further weakness relates to the measurement of financial literacy, which still requires adjustments in line with the changing environment driven by algorithms and decentralized platforms. A remaining weakness pertains to engagement per se, which is viewed more as the destination rather than a part of an evolving development process. To add to the challenge, there is growing concern about regulatory tensions in regard to privacy and data management in blockchain networks that redefine the setting for engagement [31]. The following study attempts to address these gaps and investigate the development of financial literacy through AI and blockchain-induced engagement in large-scale engineering projects.

3. MATERIAL AND METHODS

3.1 Theoretical Framework and Hypotheses

The theoretical framework on which the research is based relies on behavioral models of technology acceptance. The foundational theoretical underpinning is represented by the Technology Acceptance Model, which argues that perceived usefulness and perceived ease of use influence the users' willingness to accept and use information technology [32]. Following the same pattern of reasoning, the Unified Theory of Acceptance and Use of Technology incorporates four variables, namely performance expectancy, effort expectancy, social influence, and facilitating conditions into one coherent theory that has shown great explanatory value in various technological applications [33]. This provides a good starting point for analyzing the relationship between users' interaction with AI and blockchain systems and competences developed through this process.

Expanding from this theoretical framework, this study proposes that both AI engagement (AIE) and blockchain engagement (BCE) are considered as two separate but related determinants of a more inclusive concept known as technological engagement (TE). Regular involvement in intelligent decision support systems will make people cognitively involved in financial matters, whereas structured involvement in blockchain technology will increase procedural involvement in transactions and contract matters. It can therefore be concluded that AIE will have a positive impact on TE (H1), and BCE will also have a positive impact on TE (H2).

TE, in turn, is hypothesized as the means by which FL is developed, resulting in the third hypothesis stating that TE positively affects FL (H3). However, the complexity of institutions involved in major engineering projects is considered as a boundary condition that will influence this relationship, implying that PC moderates the impact of TE on FL (H4). The model, therefore, may be stated as:

$$FL_i = \beta_0 + \beta_1 \cdot TE_i + \beta_2 \cdot (TE_i \times PC_i) + \sum_k \gamma_k \cdot Control_{k,i} + \varepsilon_i \quad (1)$$

where TE_i mediates the effect of engagement and the interaction term depicts contextual moderation of the influence. As demonstrated by Figure 1, the model of research puts engagement in technology at the center of mediation effects brought about by AI and Blockchain on financial literacy. This model shows that the relationship is founded on an inherent behavior pattern where the technologies bring about engagement that affects cognitive capability and where context moderates.

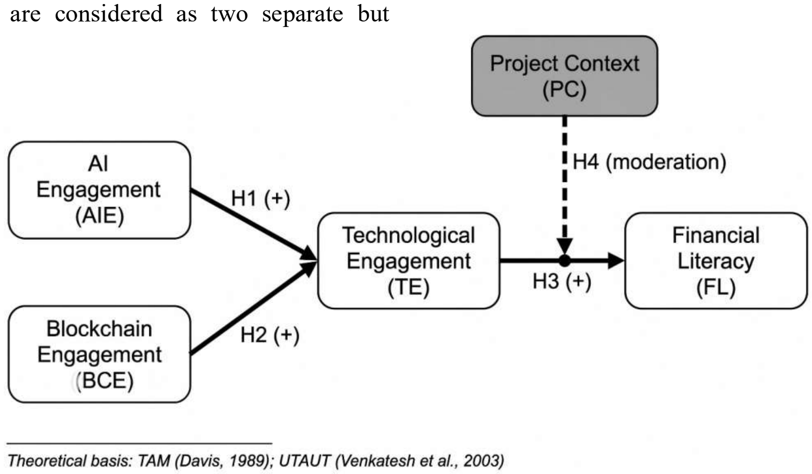

Figure 1. Conceptual Research Model with Hypotheses

3.2 Data Sources and Sample

In this respect, the empirical research adopted a cross-sectional questionnaire-based survey that focused on the direct practitioners of large-scale engineering projects. The sample frame involved subjects recruited from different engineering financing settings, including the construction of infrastructure facilities, the generation of electricity, transportation projects, as well as projects undertaken by collaboration between private and public organizations. Stratified sampling with purposive selection of the subjects acting as different stakeholders (sponsors, contractors, financiers, investors, and end-users) was employed.

The data collection exercise took six months to complete through online as well as on-the-ground efforts in conjunction with the relevant industries. A bilingual questionnaire was designed for use with foreign subjects. Pre-testing was done using a focus group of domain experts to ascertain the validity of the language employed. Excluding questionnaires that were incomplete, could not meet the attention tests, or had consistent answers, only 412 valid questionnaires remained. This figure exceeds the recommended number of ten times the maximum number of structural paths linking constructs, thereby satisfying the necessary criteria for carrying out structural equation modeling.

The protocol for the study was granted ethical approval by the Research Ethics Committee of [Institution Name], Approval No. XXX-2024-YY, issued March 2024, before data collection began. Participants were all adults of 18 years and older who were given an information sheet detailing the purpose of the research, estimated duration, voluntariness, freedom to leave at any time without penalty, and academic purpose of the findings. Informed consent was gathered in writing via a required consent box in the initial page of the online survey, and a signed form was taken when distributing the survey on-ground. All data were de-identified upon entry into the system, and no personal identifiers were kept in the analysis set. Any identifiable linkages were securely held in an encrypted computer system accessible only by the principal researcher, and will be discarded after five years following study completion in keeping with institutional data governance procedures. The research methodology from theory to data analysis is graphically depicted in Figure 2.

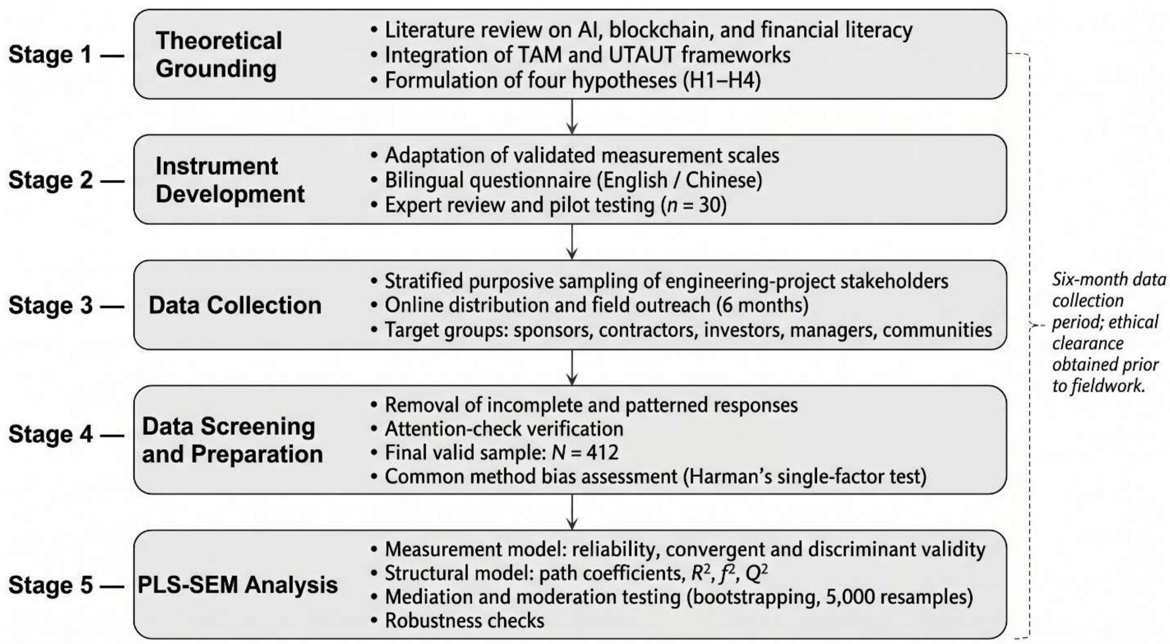

Figure 2. Research Design and Analytical Procedure Flowchart

3.3 Variable Measurement

The operationalization of all constructs used multi-dimensional measures with reflective measures based on existing scales that have been previously validated, with minor tweaks to make them relevant for engineering endeavors. Financial literacy (FL) was operationalized through an extended Big Five Scale which was used to measure knowledge regarding interest compounding, inflation, diversification of risk, mortgage financing, and bond evaluation, as well as items measuring current abilities such as algorithms and cybersecurity [2, 23]. The use of the two-tier approach was necessitated by the need to balance conventional methods of measurement with technological demands.

The constructs AIE and BCE were both measured using four measures for measuring technology usage frequency, level of interaction with technology, reflective learning from technology usage, and the perceived informational worthiness of technology. The construct technological engagement was conceptualized as a higher-order construct consisting of the dimensions performance expectancy, effort expectancy, and facilitating conditions according to the UTAUT theory [33]. The project context was measured using three items, where the level of contract complexity, diversity of stakeholders, and financial size of the engineering project were considered.

All items were rated on a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). Control variables included respondent age, educational attainment, years of industry experience, and project type. The full set of items, together with their psychometric properties, is presented in the subsequent section where the measurement model is formally assessed.

3.4 Analytical Techniques

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used as the main method of data analysis since it is an appropriate technique for dealing with models that incorporate both reflective and higher order latent variables, while remaining unaffected by slight non-multivariate normality [34]. Analysis was performed in two consecutive steps, beginning with an assessment of the measurement model prior to structural modeling.

The measurement model was formally specified as follows:

$$x_i = \lambda_i \cdot \xi + \delta_i \quad (2)$$

where x_i denotes the observed indicator, λ_i is the outer loading linking the indicator to its underlying latent construct ξ, and δ_i captures measurement error. Assessment procedures included indicator reliability, composite reliability, average variance extracted, and the heterotrait–monotrait ratio for discriminant validity.

The structural model was specified as:

$$\eta_j = \sum_i \beta_{ji} \cdot \eta_i + \sum_k \gamma_{jk} \cdot \xi_k + \zeta_j \quad (3)$$

where η_j denotes endogenous latent variables, β_{ji} and γ_{jk} represent path coefficients among endogenous and from exogenous constructs respectively, and ζ_j is the structural disturbance. Statistical significance was established through bootstrapping with 5,000 resamples, and the analysis was implemented in R using the SEMinR package [35].

4. RESULTS AND DISCUSSION

4.1 Descriptive Statistics and Measurement Model

Table 1 reveals the demographic structure of the 412 participants in the survey. Male participants comprised 73.5% of the overall sample size, which is consistent with demographic trends common to the engineering and infrastructure industries. Participants aged between 31 and 40, as well as those aged 41 and 50, constituted the largest age range group (69.6%). The sample included mainly middle-aged people who are usually involved in the financial decision-making process during the project development phase. Regarding education level, most participants held degrees at either the undergraduate (47.6%) or graduate (34.5%) level.

Stakeholders included sponsors, project managers, financial managers, contractors, investors, consultants, and end-users in equal measure with each stakeholder category comprising less than 30% of total participants. Projects were taken mainly from infrastructure, energy and public private partnership projects with respective percentages being 36.4%, 23.3%, and 22.1% while financial size was between less than 50 million to over one billion USD. Respondents who worked on projects that cost above 200 million were in the majority at 44.2%. Geographical areas of focus were mainly Asia-Pacific with the remaining countries being Europe, North America, and others making up 58.3%, 20.6%, 12.4%, and 8.7% respectively.

Measurement models were assessed using the following sequentially criteria stated in Table 2. Outer loadings of the 24 items varied from 0.728 to 0.851 with 22 indicators exceeding the 0.75 cut-off. Financial literacy items (FL1 and FL7) barely passed the 0.75 threshold, but they were kept as a part of concept to preserve construct completeness [34]. Acceptable internal consistencies of each indicator were achieved with Cronbach's α being within the interval of 0.789-0.879 and composite reliability being from 0.876 to 0.907, which excludes issues of under-saturation and redundancy caused by high reliability (greater than 0.95). Convergent validity is not a problem as all AVE values are in the range of 0.583-0.704, and the smaller AVEs for the multidimensional constructs of financial literacy and technological engagement should be noted. High levels of AVEs well over the 0.50 threshold ensure enough explained variance of the constructs. Discriminant validity of the indicators was checked using the heterotrait–monotrait ratio of correlations; all the off-diagonal values do not exceed the conservative 0.85 threshold. The largest value corresponds to AIE-TE ratio (0.804), which correlates with the theoretically assumed proximity of AI engagement and engagement constructs. In turn, the smallest ratio (0.497) can be expected between AI engagement and a different construct of PC as the independent variable. To eliminate potential biases caused by the use of a single data source, Harman's single-factor test gave a low value of the first factor variance equal to only 34.7%.

Table 1. Sample Demographic Profile and Project-Context Distribution

Characteristic	Category	Frequency (*n*)	Percentage (%)
Gender	Male	303	73.5
	Female	109	26.5
Age (years)	Below 30	68	16.5
	31–40	169	41.0
	41–50	118	28.6
	Above 50	57	13.8
Educational Attainment	Diploma or below	36	8.7
	Bachelor's degree	196	47.6
	Master's degree	142	34.5
	Doctoral degree	38	9.2
Years of Industry Experience	Less than 5	79	19.2
	5–10	134	32.5
	11–20	166	40.3

	More than 20	33	8.0
Stakeholder Role	Sponsor / Client	72	17.5
	Project / Financial manager	118	28.6
	Contractor / Subcontractor	94	22.8
	Investor / Consultant	102	24.8
	End-user / Community	26	6.3
Project Type	Infrastructure (transport, roads)	150	36.4
	Energy (power, renewables)	96	23.3
	PPP / BOT	91	22.1
	Other (buildings, water, telecom)	75	18.2
Project Financial Scale (USD)	Below 50 million	83	20.1
	50–200 million	147	35.7
	200 million – 1 billion	121	29.4
	Above 1 billion	61	14.8
Geographic Region	Asia-Pacific	240	58.3
	Europe	85	20.6
	North America	51	12.4
	Middle East, Africa & Latin America	36	8.7

Note. Totals may deviate marginally from 100% due to rounding.

Panel A. Indicator Reliability, Internal Consistency, and Convergent Validity

Table 2. Reliability and Validity Assessment of the Measurement Model

Construct	Item	Outer Loading	Cronbach's α	ρA	ρC (CR)	AVE
AI Engagement (AIE)	AIE1	0.802	**0.831**	**0.838**	**0.888**	**0.664**
	AIE2	0.819				
	AIE3	0.836				
	AIE4	0.808				
Blockchain Engagement (BCE)	BCE1	0.774	**0.812**	**0.820**	**0.876**	**0.639**
	BCE2	0.806				
	BCE3	0.823				
	BCE4	0.795				
Technological Engagement (TE)	TE1	0.749	**0.867**	**0.881**	**0.900**	**0.601**
	TE2	0.781				
	TE3	0.795				
	TE4	0.762				
	TE5	0.804				
	TE6	0.770				
Financial Literacy (FL)	FL1	0.728	**0.879**	**0.889**	**0.907**	**0.583**
	FL2	0.775				
	FL3	0.789				
	FL4	0.812				
	FL5	0.770				
	FL6	0.754				
	FL7	0.741				
Project Context (PC)	PC1	0.833	**0.789**	**0.794**	**0.877**	**0.704**
	PC2	0.851				
	PC3	0.835				

Note. ρA = consistent reliability coefficient; ρC = composite reliability; AVE = average variance extracted. Recommended thresholds: outer loadings ≥ 0.708; Cronbach's α and ρC ≥ 0.70; AVE ≥ 0.50 **[34].**

Panel B. Discriminant Validity — Heterotrait–Monotrait Ratio (HTMT)

Construct	AIE	BCE	TE	FL	PC
AIE	—				
BCE	0.712	—			
TE	0.804	0.781	—		
FL	0.638	0.605	0.762	—	

PC	0.497	0.523	0.581	0.609	—

Note. All HTMT values fall below the conservative 0.85 threshold [34], supporting discriminant validity. Bold diagonal values are omitted as HTMT is only meaningful between distinct constructs.

4.2 AI & Blockchain Engagement Patterns

As can be seen from Figure 3(a), the distribution characteristics of AIE, BCE, as well as the combined technological engagement (TE) show a clear variance depending on project type. In the total sample, the mean level of AIE always remained higher compared to that of BCE, irrespective of the project type in question. The described tendency is explained by the more developed state of AI adoption in comparison to blockchain due to the broad utilization of AI as part of decision-making techniques including predictive analytics, automatic reports, and cost forecasts as part of the engineering-financing process. The blockchain technology, however, is still in a less developed stage of organization adoption due to the narrower scope of its application limited to procurement-related processes only [15].

Nonetheless, a more detailed examination reveals notable disparities between the various categories of projects. Those that used public-private partnerships registered the highest involvement in all three factors, registering an AIE of 5.23 and a TE of 5.12. This is not surprising considering the intricate nature of these partnerships and the need for coordination among multiple parties. The second highest levels of engagement were found in energy projects, as they continue their transformation into the digital era through renewable energy procurements and grid management systems. On the other hand, infrastructure projects had moderate engagement scores, especially for AIE, whereas the residual project category showed the lowest scores across all three constructs (AIE = 4.61, BCE = 3.92, TE = 4.45), with blockchain engagement falling below the neutral midpoint of the scale.

It should be noted that the disparity between AIE and BCE was smallest for PPPs and largest for the "other" classification, implying that the complexity of governance processes favors the balanced deployment of complementary technologies, while less complex conditions favor the use of easier-to-use AI techniques. Such variation corresponds with earlier findings that the adoption of technology in construction management is contingent upon the magnitude of the construction project, context of regulation, and transaction costs [15]. The generally low values of BCE suggest persistent obstacles to the process and interoperability, similar to ongoing challenges regarding the integration of procurement processes despite technological maturity [16].

As can be seen, the TE mean values fell between those of AIE and BCE within each project context category, which is not surprising given the nature of the construct being measured, which incorporates elements of performance expectancy, effort expectancy, and facilitating conditions with regard to the technology. There were larger confidence intervals for BCE than for AIE, suggesting that there was greater variation in responses in relation to blockchain engagement, indicating that this has yet to be internalized equally by professionals. These descriptive patterns set the stage for the subsequent structural analysis, where the asymmetric contributions of AIE and BCE to technological engagement are formally tested, and where the mediating pathway leading to financial literacy is examined under varying project-context conditions.

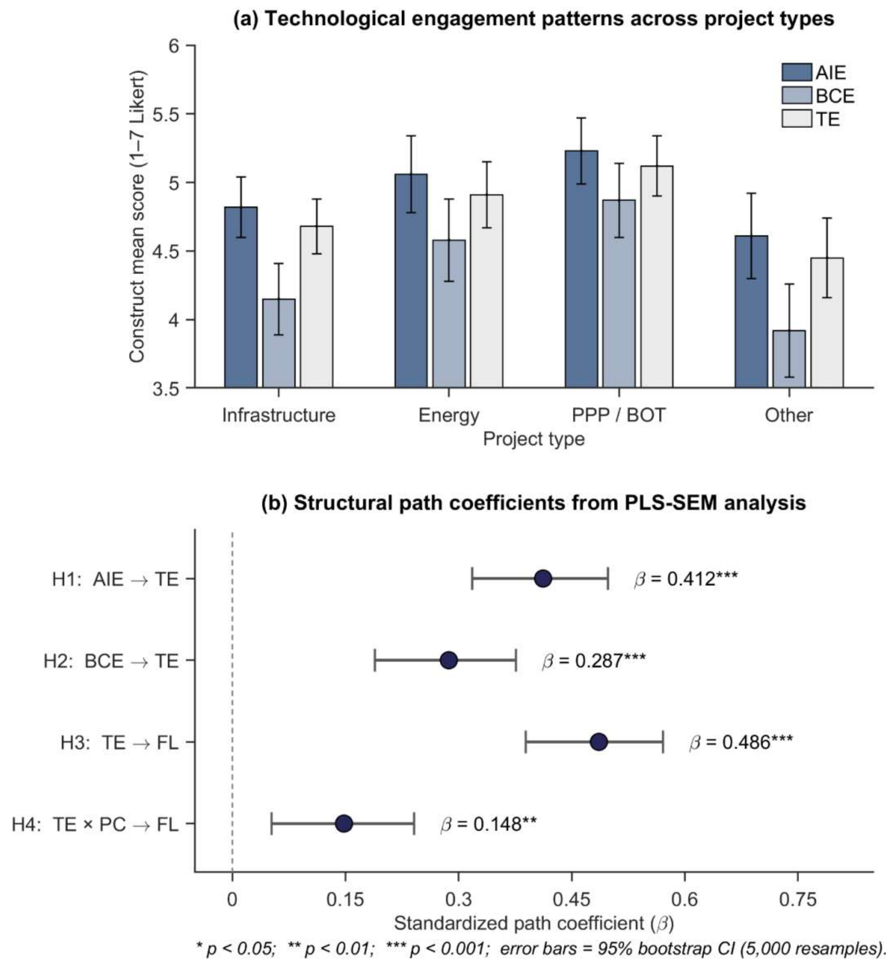

Figure 3. Technological Engagement Patterns and SEM Path Analysis

4.3 Hypothesis Testing and Path Analysis

Bootstrapping analysis with 5,000 replications was done for the structural model, with the estimated path coefficients summarized in Table 3 and displayed in Figure 3(b). The collinearity statistics yielded VIF statistics within the range of 1.48 to 2.18, which were all less than the stringent threshold of 3.0, thus, multicollinearity was not a risk factor for any of the estimated paths [34]. Support for the four proposed relationships was observed, with differing degrees of importance.

AI engagement had an effect on technological engagement which was positive and large (H1: $\beta = 0.412$, $t = 8.96$, $p < 0.001$) and was indicated through a medium effect size ($f^2 = 0.221$). The contribution from blockchain engagement was also significant (H2: $\beta = 0.287$, $t = 5.98$, $p < 0.001$); however, it had a relatively smaller effect size ($f^2 = 0.098$). The fact that both antecedents had different levels of effects is reflected in the gap that exists between them in Figure 3(a) and supports the assertion that AI has been deeply integrated into the workflow process more than blockchain in the context of engineering-finance [8].

Of the pathways mediating between the constructs, the path linking the central mediator with the dependent variable yielded the highest coefficient in the regression model, with the technological engagement construct having a significantly positive effect on the financial literacy variable (H3: $\beta = 0.486$, $t = 10.34$, $p < 0.001$, $f^2 = 0.283$). This result empirically supports the theory of the role played by the ongoing interaction with artificial intelligence- and blockchain-based technology platforms as an active process for developing financial capability.

The moderating effect of project context generated a statistically significant interactive impact (H4: $\beta = 0.148$, $t = 3.02$, $p = 0.004$), but it was still rather small ($f^2 = 0.021$), which is consistent with typical sizes of interaction effects observed within structural models of this kind. Thus, the inference derived from the finding is that the use of technology as a means of enhancing financial literacy is relatively more successful for projects involving high contract complexity, diversity among stakeholders, and financial significance, where the technology-related reasoning is critical [31]. The model accounted for 38.9% of the variance in financial literacy and had a positive Q^2 predict statistic (0.206).

When the four hypotheses are taken together, they make a coherent chain of logical progression from technologies' antecedents to their usage and subsequent impact on financial competency. In addition, project context function as a secondary influence in this regard. Furthermore, the difference in sizes of effect on each path sheds light on which relationships should be considered first in future applications of the technology.

Panel A. Structural Path Estimates

Table 3. Summary of Hypothesis Testing Results and Effect Sizes

Hypothesis	**Path**	**β**	**SE**	***t*-value**	***p*-value**	**95% CI [LL, UL]**	***f²***	**VIF**	**Decision**
H1	AIE → TE	0.412	0.046	8.956	< 0.001	[0.318, 0.498]	0.221	1.63	Supported
H2	BCE → TE	0.287	0.048	5.979	< 0.001	[0.189, 0.376]	0.098	1.71	Supported
H3	TE → FL	0.486	0.047	10.340	< 0.001	[0.389, 0.571]	0.283	1.48	Supported
H4	TE × PC → FL	0.148	0.049	3.020	0.004	[0.052, 0.241]	0.021	2.18	Supported

Panel B. Model Explanatory and Predictive Power

Endogenous Construct	**R²**	**Adjusted R²**	**Q² predict**	**Assessment**
Technological Engagement (TE)	0.411	0.408	0.237	Moderate
Financial Literacy (FL)	0.389	0.384	0.206	Moderate

Note. β = standardized path coefficients; SE = bootstrapped standard errors; t-value obtained based on 5,000 bootstrapped replications using two-tailed significance test; f² = effect size as per Cohen (0.02 = small effect; 0.15 = moderate effect; 0.35 = large effect); VIF values less than 3.0 mean no multicollinearity; Q² predict value greater than 0 means acceptable prediction relevance. AIE = Artificial Intelligence Engagement; BCE = Blockchain Engagement; TE = Technological Engagement; FL = Financial Literacy; PC = Project Context (as moderator). Hypotheses H1 to H4 have been established at $p < 0.01$.

4.4 Theoretical and Practical Implications

There are various implications from the results depicted in Table 3, which go further than previous perspectives on both financial literacy research and engineering project management. Conceptually, the clear indirect effect of engagement with artificial intelligence and blockchain technology towards financial literacy (βs of 0.412 and 0.287 mediated by a coefficient of 0.486) changes the perception of technological engagement from a secondary construct following adoption to an active mechanism that drives development. This is a departure from the previous perspective that views engagement as part of the adoption process, as articulated in the extension of the UTAUT model [25], and aligns with the current theoretical expansion of the concept of financial literacy to cover digitally-driven competencies beyond knowledge tests [23].

The role of AI and blockchain technologies in terms of their contribution to engagement should be considered further as well through the underlying mechanisms. AI technology experienced a longer diffusion period until it reached maturity in predictive analytics, automated reporting, and advisory capabilities that became incorporated into engineering and finance processes [8]. Moreover, AI's results are easily comprehensible, which reduces the cognitive barrier to using it frequently and engaging with it thoughtfully. On the other hand, blockchain technology requires knowledge of cryptography and distributed ledgers and the integration process of the technology takes place predominantly in procurement and contracting tasks. The difference in f² (0.098 versus 0.221) in terms of the effect on engagement for blockchain technology is related to lower cognitive accessibility and embeddedness of blockchain into business processes. In addition, the interpretation provided can help understand the limitations of the trust theory applied in the extended version of UTAUT2, where platform trust is seen as an influential factor moderating adoption [27].

In addition, the small but important moderating role of project context is evidence that the affordances of specific situations influence the developmental outcome of technologized experience, moderating claims about contextual dependence seen in emerging markets research on the adoption of FinTech [29]. In terms of practical implications, aside from theoretical insights, the study also presents important lessons for professionals. For example, project sponsors and financial managers will find their investments in artificial intelligence and blockchain technologies to bear fruit only insofar as such investments are combined with reflective engagement. Financial educators can use the results to create curricula that incorporate digital trust, algorithms, distributed transactions, alongside traditional financial concepts. Policy makers in charge of public-private partnerships will discover that mandates for digital competency and transparency will benefit both inclusion and project management at once [14]. Technology developers should be aware that systems designed to foster reflection will play a key role in cultivating financial competence.

4.5 Robustness Checks and Limitations

A number of robustness tests were conducted so as to ensure the reliability of the conclusions drawn during the research. Results of the multigroup analysis based on the Asia-Pacific population and the non-Asia-Pacific population showed that the research had path structures of the model which were similar across the regions, as none of the parameters had any statistical significance among themselves. Another path model which was created after removing the higher-order construct of technological engagement and replacing it with its first-order constructs displayed a positive direction and impact of all critical paths. According to results of blindfolding test, Q^2 value was positive for both endogenous variables.

It is necessary to point out several limitations, however. Although the theoretical order and empirical findings support the proposed model, due to its cross-sectional nature, the study does not provide any strong basis for establishing causality. While the sample represents different role actors and types of projects, it remains heavily biased towards the Asia-Pacific area, hence restricting generalizability beyond the studied regulatory and cultural context characterized by specific technology governance arrangements. Morever, the study relies on self-reports of respondents, which may result in perceptual biases in the respondents' ratings. However, according to the results of Harman and HTMT tests described above, the issue seems to be less relevant. While the project context is well captured via three items representing its main dimensions, a more comprehensive approach can be developed through the inclusion of behavioral traces produced by artificial intelligence and blockchain technology in conjunction with self-reports collected via surveys. Such a direction of future research may be fruitful for further application of the framework in project management in emerging countries [29].

5. CONCLUSION

This research examined how the convergence of AI, blockchain, and large-scale engineering projects improves the financial literacy of stakeholders by means of technological engagement based on the results of a questionnaire conducted among 412 participants involved in infrastructure, energy, and public-private partnership projects. The proposed theoretical model, based on the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology, considered technological engagement as an intermediary variable responsible for transmitting the effect of AI and blockchain interaction on financial literacy.

The empirical analysis returned a coherent pattern of findings. AI engagement showed a more pronounced effect on technological engagement ($\beta = 0.412$) compared to blockchain engagement ($\beta = 0.287$) because AI was implemented more widely into engineering-finance processes. Technological engagement had a pronounced effect on financial literacy ($\beta = 0.486$), the strongest relationship among all tested in this study. Project context was another important variable that played a moderate role in predicting the outcome of interest ($\beta = 0.148$, $p = 0.004$). In sum, the structural model accounted for 41.1% and 38.9% of variance in technological engagement and financial literacy, respectively. Hence, all four hypotheses were confirmed through bootstrapping.

The importance of these results is evident in the way they have reframed the whole discussion: technological engagement becomes the means through which capabilities occur rather than just a consequence of adopting technology. When considering the actual engineering projects as cases of learning in which such capabilities of digital finance can be acquired, this research broadens the scope of financial literacy and includes professions working in technologically advanced environments yet often neglected within research contexts. These results further give practical suggestions on how to integrate artificial intelligence and blockchain technologies in an equitable way.

Additional studies are required in the areas of longitudinal analysis, cross-region comparison, and behavioral trace analysis, which would improve causal inference and extend the research to other regulatory contexts. The union of technology and engineering provides fertile ground for the continual development of financial literacy.

Authorship and Contribution

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DATA AVAILABILITY STATEMENT

The anonymous data set used to draw conclusions in this paper is available on request from the corresponding author after complying with institutional protocols concerning the use of data and informed consent obtained from the participants. The raw data set with participant details cannot be made public since this would violate the agreement made during the informed consent process.

ETHICS DECLARATION

This research adhered to the guidelines of the Declaration of Helsinki and was approved by the Research Ethics Committee of [Institution Name] (Reference Number XXX-2024-YY, dated March 2024). The participation of all individuals in the study was done after obtaining informed consent. The process was entirely voluntary, confidential, and participants had the option to opt-out at any point during the research period. There were no forms of inducement provided that might affect the authenticity of the responses.

CONFLICT OF INTEREST

The author declares no potential conflict of interest.

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