

An Integrated Trust–Motivation–Value Framework for Blockchain-Enabled AI-Based Gamification Adoption in Education

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Abstract

The rapid digital transformation of education has intensified the adoption of artificial intelligence (AI), gamification, and blockchain to address challenges related to learner engagement, transparency, data security, and sustainable educational governance. While AI-based gamification enhances personalization, feedback, and motivation, concerns surrounding trust, data integrity, and the credibility of digital rewards continue to hinder large-scale adoption. Blockchain technology offers a decentralized and transparent infrastructure capable of strengthening trust and ensuring the reliability of AI-driven gamified learning environments. However, empirical research examining the combined effects of blockchain, AI, and gamification on adoption behavior remains limited. Addressing this gap, this study proposes an Integrated Trust–Motivation–Value (TMV) framework to explain users' adoption of blockchain-enabled AI-based gamification in education. Grounded in trust theory, self-determination theory, and perceived value theory, the proposed model conceptualizes blockchain features (security, transparency, decentralization, and data integrity) as antecedents of trust, and gamification elements (points, badges, leaderboards, rewards, collaboration, and enjoyment) as drivers of learner motivation. Trust and motivation are theorized to influence users' perceived value, which subsequently determines adoption intention. A quantitative, cross-sectional survey design was employed, and data were collected from learners with experience using AI-based digital learning platforms. The proposed model was empirically tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results reveal that blockchain features significantly enhance trust, while gamification elements strongly promote motivation. Both trust and motivation positively influence perceived value, which emerges as a key predictor of adoption intention. The study contributes theoretically by integrating trust and motivation into a unified value-based adoption framework for blockchain-enabled AI-based gamification. Practically, the findings offer guidance for educators, policymakers, and system designers to develop secure, transparent, and motivating digital learning ecosystems that support sustainable educational transformation.

1. Introduction

The rapid advancement of digital technologies has fundamentally transformed contemporary education systems, reshaping how teaching, learning, and assessment are designed and delivered. Traditional educational models, which rely heavily on centralized administration, manual record keeping, and standardized instructional practices, increasingly struggle to address issues of learner engagement, data security, transparency, and scalability in digitally mediated learning environments [1], [2]. As education systems worldwide move toward sustainability-oriented digital transformation, there is growing demand for innovative technologies that not only enhance learning outcomes but also ensure trust, accountability, and long-term institutional resilience [3]. In this context, artificial intelligence (AI), gamification, and blockchain have emerged as three transformative technologies with significant potential to redefine educational governance and learning experiences[4], [5].

Artificial intelligence is at the core of new developments in education, helping to develop adaptive learning systems, intelligent tutoring, automated feedback and decision-making-based data [6]. AI-powered educational platforms offer options for personalized learning path assignment, predictive analytics of the learning performance of the learner, and active observation of engagement through the means of real-time monitoring. The involvement of the platform can enhance efficiency and inclusiveness [7], [8]. Nevertheless, despite the advantages of artificial intelligence-based education, constraints in algorithm transparency, data privacy and security, ethical governance and trust in automated decision making, impede the widespread adoption of the same [9]–[11]. These challenges necessitate complementary technological infrastructures to enhance the transparency, security and confidence of stakeholders in AI-based learning. Moreover, the Gamification is broadly a pedagogical approach that was informed by psychology and designs games and game-like strategies to improve learner motivation, engagement, and persistence by harnessing the power of games and design elements within a non-game context [12], [13]. When gamification is properly designed and aligned with learning objectives, it has proved to positively influence students' intrinsic motivation, learning satisfaction and academic performance in an educational setting [14], [15]. Nonetheless, traditional gamified approaches are based on one central organization, and call into question the fairness of the system, manipulation of rewards, credibility of achievements, and sustainability of motivation [16]. Gamified experiences may lose value for learners and lessen their intention to use it due to these limitations.

According to [17], [18], the use of Blockchain technology presents a great opportunity to overcome these systemic limitations through a decentralized immutable and transparent infrastructure for educational data and digital rewards. According to Ramos et al. [19], trust between involved parties, such as students, educators, institutions, and others, can be improved with the use of blockchain. This is a technology that allows learning records and verifiable credentials to be securely stored and tracked, as well as achievements to be tamper-proofed. The incorporation of AI-based gamification with blockchain can enhance the credibility of reward systems and ensure the integrity of data while assisting in the sustainable governance of the digital ecosystem for learning [13], [20].

To conceptualize this integration, the present study proposes three complementary conceptual models that collectively explain how artificial intelligence, gamification, and blockchain operate as a unified educational ecosystem in higher education (See Fig. 1 Proposed Architecture of Blockchain-Enabled AI-Based Gamification in Education). First, a system-level architecture illustrates the technical interaction between AI-driven personalization, gamified learning mechanics, and blockchain-based trust infrastructure. Second, a process-flow framework explains how learner data, AI analytics, gamification outcomes, and blockchain verification interact dynamically throughout the learning lifecycle. Third, a theoretical adoption framework captures the psychological and value-based mechanisms through which blockchain features and gamification elements influence trust, motivation, perceived value, and adoption intention. Together, these models provide a holistic view that links technological design, learner experience, and behavioral outcomes, addressing a critical gap in prior literature that has largely examined these technologies in isolation.

Even with the aforementioned theoretical benefits, there is a dearth of empirical studies related to the implementation of blockchain-enabled AI-based gamification in the field of education. This holds true especially with relation how the various blockchain characteristics and gamification mechanisms work together in order to influence the users' perception as well as adoption intention.

Figure 2 depicts the operational flow of blockchain-enabled AI-based gamification in higher education. The framework demonstrates how learner interactions generate educational data that are analyzed by AI engines to personalize learning experiences and trigger gamified incentives. These incentives and learning achievements are subsequently validated and recorded on the blockchain, ensuring transparency, trust, and tamper-proof certification while feeding back into AI models for continuous optimization.

Figure 2. Operational Flow of AI-Based Gamification Supported by Blockchain

Most existing studies analysed AI, gamification and blockchain as stand-alone innovations in education, focusing solely on their respective benefits, e.g., personalization, motivation boosting; and secure credentialing [19]–[22]. Even though these studies are insightful, they ignore the many technological trust mechanisms and motivational processes that shape users' perceived value and usage behavior. Furthermore, previous studies often emphasize technical feasibility or pedagogical effectiveness while not sufficiently examining the psychological and value-based pathways through which learners and educators evaluate and accept blockchain-enabled gamified that facilitate learning [23]. The division in the literature leads to a gap in understanding how trust, motivation, and perceived value jointly impact adoption intention in AI-supported and blockchain-driven gamified education.

To bridge this shortcoming, the current research presents An Integrated Trust–Motivation–Value Framework for Adoption of Blockchain-Enabled AI-Based Gamification. This study theorizes trust and motivation as mediating mechanisms by drawing upon trust theory, self-determination theory, and perceived value perspectives. Blockchain features and gamification elements influence perceived value and adoption intention. The key features of blockchain technology such as security, transparency, data integrity and decentralization offers great potential for enhancing trust in institutions and technologies. Gamification elements such as points and badges, leaderboards, rewards and feedback, collaboration and enjoyment, are theorised to generate more motivation among learners [16]. As a result, the users' perceived trust and motivation shapes their perceived value of the blockchain-enabled AI-based gamification system, which shapes the intention to adopt and continue using the system [24], [25]. The Integrated Trust–Motivation–Value Framework for Adoption of Blockchain-Enabled AI-Based Gamification. Grounded in trust theory, self-determination theory, and perceived value theory, the model explains how blockchain features (security, transparency, decentralization) enhance trust, while gamification elements stimulate learner motivation. Trust and motivation jointly shape perceived value, which ultimately determines adoption intention and continued system use.

The importance of this research article The idea behind the current study is to contribute to the literature on the adoption of educational technology by integrating trust and motivation in a single value-based model. It helps extend the traditional models of acceptance restricting them to a usability or performance expectancy. The study helps to enhance our understanding of how cognitive and affective evaluations drive adoption by elevating perceived value as a core explanatory concept. The results could help schools, policymakers, and tech developers build secure, transparent, and motivating gamification systems based on the blockchain for use in education. Through the proposed framework, students will establish trustworthy and resilient digital education ecosystems while establishing education and society sustainability with a long-term prospect.

In light of these motivations, this research looks at the following research objectives: to study how blockchain features impact trust on AI-based gamification; to study how gamification features impact learner motivation; to analyze the role of trust and motivation on perceived value; and to analyze the impact of perceived value on adoption intention of blockchain-enabled AI-based gamification in education. With this in mind, the current study seeks to investigate how and why trust and motivation are critical mechanisms linking design features of technology to adoption behaviour.

The following is the scheme of this paper. The next section drives the theoretical foundations and develops the hypothesis of the study. The methodology section describes a research design, measurement, and data analysis using structural equation modelling. The result section brings forth the findings of the research. Next, we will discuss both the theory and practical view of our findings. To summarize, this research paper contains limitations and future research suggestions.

2. Literature Review and Theoretical Framework

As education continues to embrace advanced digital technologies, theoretical models that simultaneously capture the affordances of these technologies, as well as the human-centred mechanisms driving users’ acceptance, are increasingly needed. A complex socio-technical innovation that utilizes intelligent design, automated algorithms, and decentralized trust infrastructures is blockchain-based AI gamification. A multifaceted theoretical lens that explains the cognitive and affective evaluation of such systems must be used to comprehend its adoption. Utilizing the existing corpus of educational technology research, the present study draws on Trust Theory, Self-Determination Theory (SDT), Perceived Value Theory and the Technology Acceptance perspective to explain adoption intention via trust, motivation and perceived value.

Various technology adoption models such TAM and UTAUT have been successful in enabling valuable insights into users’ behavioral intentions. However, they continue to underestimate trust risk and motivational dynamics underlying the adoption behaviour, especially in AI-enabled blockchain -supported scenarios [26], [27]. When it comes to education and there is sensitive learner data, assessment integrity, and ethical AI governance, trust and motivation then become determining factors shaping perceived value and long-term adoption. The study presents an integrated framework (as illustrated in Fig. 3), where blockchain features and gamification element serve as antecedents of trust and motivation, which then results in perceived value and intention to adopt.

Figure 3. Proposed Research model: *This figure presents illustrating the relationships among blockchain features and gamification features. Trust and motivation act as mediating constructs influencing perceived value, which in turn determines users’ adoption intention toward blockchain-enabled AI-based gamified education.*

To clarify the theoretical contribution of this study and to avoid overlapping with organizational-level frameworks (i.e., TOE or RBV), this paper operationalizes user-level cognitive and motivational mechanisms. This paper draws on recent calls for adoption models rooted in psychology [6]. Table 1 systematically maps the theoretical bases, study constructs and hypotheses of the research.

Table 1
Mapping of Theoretical Foundations to Study Constructs and Hypotheses

Theory	Core Constructs	Study Variables	Hypotheses
Trust Theory (Technology & Institutional Trust)	Reliability, integrity, transparency	Security, Transparency, Data Integrity, Decentralization → Trust	H1–H4
Self-Determination Theory (SDT)	Competence, Relatedness, Autonomy	Points & Badges, Leaderboards, Rewards & Feedback, Collaboration, Enjoyment → Motivation	H5–H9
Perceived Value Theory	Cost–benefit evaluation	Trust, Motivation → Perceived Value	H10, H11
Technology Acceptance (Value-based TAM)	Behavioral intention	Perceived Value → Adoption Intention	H12

2.2 Hypotheses Development

2.2.1 Blockchain Features and Trust

The adoption of technology is significantly affected by trust. In particular, digital environments, characterised by uncertainty, automation and data, mediate technology adoption through trust. Trust Theory elucidates the process through which users develop trust towards a system. In particular, individuals develop a belief that the system is reliable and secure and most importantly, it will act according to the user’s best interest [24], [25]. In educational systems based on AI, trust plays an even greater role through opaque algorithmic decision-making and anxiety over the misuse of learner data [28]. According to Tan et al. [29], blockchain technology is a well-acknowledged trust-enabling infrastructure because of its decentralized structure, cryptographic security, and immutable records. Security is the degree of isolation of a system for the user’s data from malicious hackers. In learning contexts, AI tools constantly collect and analyze data about learners so your security is the users’ first priority. According to Suleiman et al., [30], blockchain system security is assured with the help of encryption, distributed consensus, and tamper-resistant ledgers for reduced perceived risk. Earlier studies show that perceived

security increases trust in blockchain-based digital services. Consequently, this study proposes: *H1: Security positively influences trust in blockchain-enabled AI-based gamification systems.*

Transparency is defined as the extent of visibility and understandability of system processes, data flows and outcomes to the user [13]. The absence of transparency in AI-driven educational systems makes them questionable and learners might reject them when they are unable to verify the outcomes of assessments or awards allocations. The ledger of blockchain helps to keep the track of achievements, rewards and learning materials' users can verify samples independently to ensure fairness and accountability [31], [32]. Evidence from multiple studies indicates that trust in digital learning systems increases due to transparency. Consequently, *H2: Transparency positively influences trust in blockchain-enabled AI-based gamification systems.*

Data integrity is the quality of data being accurate, consistent and reliable. To ensure confidence of institutions and learners, educational records, credentials, and gamified rewards should remain unchanged. This record cannot be altered retrospectively due to blockchain technology, which is essential for securing AI-generated assessments and tracking gamified achievements [33], [34]. Blockchain-based education research show that the data integrity is an important antecedent of trust. Consequently, *H3: Data integrity positively influences trust in blockchain-enabled AI-based gamification systems.*

Decentralization mitigates dependence on a single authority by distributing control in a network. Decentralization within an education system reduces the bias of educational institutions, increases the autonomy of learners, and reduces concern over one-sided manipulation of rewards or credentials. Decentralized governance structures are capable of enhancing institutional trust and system legitimacy [33], [35]. Accordingly, *H4: Decentralization positively influences trust in blockchain-enabled AI-based gamification systems.*

Collectively, these relationships form the blockchain–trust mechanism illustrated in Fig. 5, highlighting trust as a core mediator in the proposed framework.

2.2.2 Gamification Features and Motivation

Motivation is the key driver of learner engagement and persistence in digital learning environments. According to Self-Determination Theory (SDT), which was formulated by Deci and Ryan in the years 1985 and 2000, it posits that motivation stems from competencies, relatedness as well as autonomy. According to Hamari et al. [16], gamification characteristics are purposefully designed to instigate these needs. Therefore, this renders SDT as a theoretically confirmed lens of motivational effects regarding AI-driven gamified education as Gamification features and SDT theory are relationships described in Fig. 4.

Figure 4. Gamification features and SDT theory relationships: *This figure depicts the conceptual mapping between gamification features and the core psychological needs of Self-Determination Theory (SDT)*

The competence signals are conveyed by points and badges that notify learners of their advancement and accomplishment. When combined with AI analysis and blockchain authenticity, these rewards have more credibility and then learners feel like they have mastered skills [15], [36]. Gamification works best when points and badges are utilized to motivate learners (Sailer et al., 2017). Therefore, *H5: Points and badges positively influence motivation toward AI-based gamification.*

Leaderboards can introduce social comparison and competitive dynamics, which can further enhance competence motivation if designed ethically. Leaderboards backed by the blockchain will improve fairness and transparency, reducing manipulation concern. Prior research shows that leader boards make users more motivated when their trust in the system is high [13], [37]. Accordingly, *H6: Leaderboards positively influence motivation toward AI-based gamification.*

Rewards and feedback, especially when generated with the help of AI-based personalization provide continuous reinforcement and adaptive feedback. Reward mechanisms ensuring credibility through blockchain have long-term motivational impacts [38]. As a result, *H7: Rewards and feedback positively influence motivation toward AI-based gamification.*

Collaboration meets the SDT need for relatedness through peer interaction and shared success. Collaboration tracked by blockchain can be fair and AI will form intelligent groups and give feedback[39], [40]. Accordingly, *H8: Collaboration positively influences motivation toward AI-based gamification.*

Enjoyment reflects internal motivation based on autonomy and voluntary engagement. Gamified artificial intelligence systems that empower learners to control their own pace, pathways, and rewards significantly enhance enjoyment [15], [41]. Consequently, *H9: Enjoyment positively influences motivation toward AI-based gamification.*

2.2.3 Trust, Motivation, Perceived Value, and Adoption Intention

The theory of perceived value explains how consumers evaluate a product based on the benefits and costs they expect to measure whether they will buy it or not. Perceived value in digital education encompasses the functional, emotional, and ethical aspects of an offer and characterises factors such as trust and motivation[42]. As per [43], trust reduces perceived risk while the motivation increases emotional benefit as well as experience benefit which in turn enhances perceived value. The trust in blockchain-enabled AI systems assures users about the security, fairness, and reliability of their data, this can create a positive perceived value [44], [45]. Likewise, motivated learners are more likely to regard these gamified systems as beneficial and worthwhile, reinforcing value perceptions [46]. Ultimately, the intention to adopt indicates the users' willingness to use a system and to continue using it. According to Venkatesh et al. [26], perceived value is a direct predictor of an individual's behavioral intention. According to this perspective.

H10: Trust positively influences perceived value of blockchain-enabled AI-based gamification.

H11: Motivation positively influences perceived value of blockchain-enabled AI-based gamification.

H12: Perceived value positively influences adoption intention of blockchain-enabled AI-based gamification.

Figure 3 (Research Model) and 5 (Hypothesized Relationships) give a full structural representation of trust, motivation and perceived value for their adopted model.

3. Research Methodology

3.1 Research Design

The proposed integrated trust-motivation-value framework for blockchain-enabled AI-based gamification adoption is empirically investigated using quantitative research design. According to Hair et al., [47], quantitative methods suit best for the theory testing and model validation in case of hypothesized complex causal relationships between latent constructs. In alignment with existing studies on the adoption of educational technologies and artificial intelligence (AI), the researchers used a cross-sectional survey approach to gather perceptual data on respondents at a point in time [48]. Hypothesis testing and statistical generalization have been enhanced with the practical generalizability of time and resources. The proposed model's exploratory–predictive nature and the presence of several latent constructs linked by mediating relationships warranted the study to adopt Structural Equation Modeling (SEM) as the major analytical tool. The estimation of measurement and structural models is simultaneous in SEM. It has significantly better explanatory power than regression-based techniques [49]. Reflecting contemporaneous studies of AI, blockchain, and gamification in education and industry, this work adopts Partial Least Squares SEM (PLS-SEM) due to its flexible nature with regard to distributional assumptions and predictive capability [50].

3.2 Population, Sample, and Data Collection

The targeted population for this research is higher education institutions of Saudi Arabia. that are making progressive innovations by adopting the AI-enabled digital training and gamified learning system. In light of the national digital transformation agenda associated with Vision 2030, Saudi Arabia is a pertinent empirical setting. This agenda promotes the adoption of artificial intelligence, blockchain integration and workforce training for sustainable and educational development [51]. A structured questionnaire survey was used to collect data (electronically and manually for broad participation). In this research, the we employed a non-probability purposive sampling method as the respondents must have pre-exposure of digital learning platforms, AI based systems and gamified training environments. This approach is in line with earlier research on adoption that essentializes domain-specific knowledge for providing meaningful responses[52], [53]. A complete of 300 valid responses were collected and retained for analysis. The sample size exceeds the minimum required by PLS-SEM analysis, including the “10-times rule” and most recent power analysis [47]. Furthermore, a sample size of 300 is statistically sufficient for bootstrapping and mediation, resulting in proper parameter estimation via bootstrapping. Formal approval was secured from Al Jouf University (Ref: DGSSR-2025-NF-03-005), and written informed consent was obtained from all participants. Anonymity and confidentiality were ensured, with respondents informed about their rights and the intended academic use of their data.

3.3 Survey Instrument Development

3.3.1 Measurement Scale and Questionnaire Design

To develop the survey, the researchers reviewed previously validated scales on blockchain adoption, AI trust, gamification, motivations, and perceived value. In the SEM study, the constructs were all measured with the help of multi-item reflective scales. Hair et al. [49] believe that this is the best practice for SEM. The items were adjusted to the context of blockchain-enabled AI-based gamification, while retaining their original meanings. All of the items were measured on a five-point Likert-type scale from 1 = strongly disagree to 5 = strongly agree. The reliability of the Likert scale makes it easier to interpret, and it is also suitable for Latent Variable Modelling [54]. Table 2 provides a summary of the measurement structure showing the codes of the constructs, examples of items and the number of items for each construct.

Table 2
Measurement Constructs and Items

Construct	Code	Item Codes (Examples)	No. of Items
Security	SEC	SEC1, SEC2, SEC3	3
Transparency	TRANS	TRANS1, TRANS2, TRANS3	3
Data Integrity	DI	DI1, DI2, DI3	3
Decentralization	DEC	DEC1, DEC2, DEC3	3
Trust in Blockchain System	TRUST	TRUST1, TRUST2, TRUST3, TRUST4	4
Points & Badges	PB	PB1, PB2, PB3	3
Leaderboards	LB	LB1, LB2, LB3	3
Rewards & Feedback	RWD	RWD1, RWD2, RWD3, RWD4	4
Collaboration	COLLAB	COLLAB1, COLLAB2, COLLAB3	3
Perceived Enjoyment	ENJOY	ENJOY1, ENJOY2, ENJOY3	3
Motivation	MOT	MOT1, MOT2, MOT3, MOT4	4
Perceived Value	PV	PV1, PV2, PV3	3
Adoption Intention	AI	AI1, AI2, AI3	3

3.3.2 Content Validity and Pilot Testing

To establish the content validity of the survey instrument, it was sent to five experts in educational technology, AI system, blockchain, and quantitative research for evaluation. Specialized experts assessed clarity, relevancy, and construct according to standard instrumental validation procedure. Some wording changes were made based on the feedback to improve clarity and appropriateness. A pilot study was conducted on 30 respondents drawn from the target population to test the reliability and clarity of items. According to preliminary reliability analysis, all constructs surpassed the recommended value of 0.70 for Cronbach's alpha which indicates internal consistency [55]. As no major issues were found, the questionnaire was moved to full study.

3.4 Data Analysis Procedure

There are various reasons for selecting PLS-SEM as the main data analysis technique. The first research aim is to predict adoption intention and explain variance in perceived value using several mediators. This first research aim is consistent with the main predictive orientation of PLS-SEM [47]. Furthermore, the present research used PLS-SEM approach as it fits best for complex models with many constructs and indicators. PLS-SEM, according to Al-rahimi et al. [56], does not require multivariate normality. Thus, it is suitable for survey-based data obtained from various industries. The examination was conducted through the SmartPLS 4, apparently having refined capabilities for model estimation, bootstrapping and predictive assessment, and seriously recommended in current IS and educational technology studies.

3.4.1 Measurement Model Assessment

The measurement model is evaluated through reliability and validity. Based on the threshold value exceeding 0.70 as being acceptable [47] internal consistency reliability will be checked using Cronbach's alpha and composite reliability (CR) Convergent validity, as measured by AVE, was satisfactory because the AVE extracted was greater than 0.50. Discriminant validity was judged using the

Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratio in accordance with recent methodological advice [57]. With these procedures, each construct in the model is ensured to be empirically distinguishable from others.

3.4.2 Structural Model and Bootstrapping

The evaluation of the structural model was a partial least squares structural equation modelling (PLS-SEM) method. The bootstrapping procedure was used for 5000 resamples to get β values (path coefficients), t-statistics, and p-values [47]. Moreover, R^2 values were assessed to assess the explanatory power of the model. In contrast, effect sizes (f^2) were reviewed to measure individual exogenous construct contributions.

3.5 Ethical Considerations

The ethical standards were strictly followed throughout the research process. Participation was voluntary, and the respondents were informed about the study's purpose; also, confidentiality was assured and they could back out at any moment. The study did not include any personally identifiable information and all information was anonymized. The research adhered to institutional ethical guidelines. Also, it complied with the application of international research ethics in social science research [58].

4. Results

4.1 Demographic Information of Participants

The study collected 300 valid responses from university students enrolled in higher education institutions in Saudi Arabia as shown in Table 3. As the diversity of the students' profile (gender, age, academic level, exposure to digital technologies) can justify the use of SEM on the data obtained from the questionnaire. The sample population was 68.0% male students, and 32.0% female students, which was a good reflection of what is currently prevailing in technology oriented academic programs. According to the data, the majority of respondents were between 26 and 35 years old (38.3%) and between 18 and 25 years old (14.7%). The high number of respondents of this age indicates that undergraduate and postgraduate learners are actively involved in the digital learning environment. Regarding educational qualifications, 46.7% had bachelor's degrees, 36.0% were pursuing master's degrees or had already completed them, and 17.3% were doctoral or professional students. Most appropriately, 78.0% reported previous experience with AI-based systems, 72.3% used gamified learning platforms, while 61.7% reported knowledge/usage of blockchain-enabled system. The overall profile shows that the respondents were digitally literate enough to assess trust, motivation, perceived value and adoption intention towards blockchain-enabled AI-based gamification in higher education meaningfully.

Table 3
Demographic Characteristics of Respondents

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	204	68.0
	Female	96	32.0
Age (years)	18–25	44	14.7
	26–35	115	38.3
	36–45	102	34.0
	Above 45	39	13.0
Education Level	Bachelor's degree	140	46.7
	Master's degree	108	36.0
	Doctorate / Professional	52	17.3
Prior AI-Based System Experience	Yes	234	78.0
	No	66	22.0
Prior Gamified Learning Experience	Yes	217	72.3
	No	83	27.7
Prior Blockchain System Awareness / Use	Yes	185	61.7
	No	115	38.3

4.2 Measurement Model Results

The measurement model of the study was first evaluated to assess the reliability and validity of the constructs followed by the evaluation of the structural model through the two-step approach recommended for PLS-SEM [47], [59]. The SmartPLS 4 application was used to evaluate the reflective measurement model, which is defined by indicator reliability (factor loadings), internal consistency reliability, convergent validity, and multicollinearity (VIF).

4.2.1 Indicator Reliability and Factor Loadings

We measured the reliability of indicators via the standardized factor loadings of variables. As per the study by Hair et al. [47], factor loadings of more than 0.70 signify that the individual indicators respectively explain a significant amount of their constructs' variance. In new and exploratory research context, loadings more than 0.60 are accepted. As depicted in Table 4, all measurement items have or exceed loading of 0.71 and are significant at $p < 0.001$. This means all indicators are significantly contributing to their respective latent construct and thus were stayed for further analysis. According to Amjad et al. [54], high reliability of indicator is imperative as states that many studies which integrate new-fangled technologies (i.e. Blockchain and Gamification) have not fully developed constructs.

Table 4
Measurement Model Results: Factor Loadings and VIF Values

Construct	Item Code	Factor Loading*	VIF
Adoption Intention	AI01	0.888	1.961
	AI02	0.849	1.851
	AI03	0.858	1.975
Collaboration	COLLAB01	0.872	1.900
	COLLAB02	0.755	2.004
	COLLAB03	0.839	1.290
Decentralization	DEC01	0.743	1.334
	DEC02	0.851	1.668
	DEC03	0.820	1.487
Data Integrity	DI01	0.867	1.733
	DI02	0.842	1.740
	DI03	0.807	1.559
Perceived Enjoyment	ENJOY01	0.785	1.466
	ENJOY02	0.808	1.521
	ENJOY03	0.832	1.412
Leaderboards	LB01	0.827	1.714
	LB02	0.892	2.148
	LB03	0.860	1.881
Motivation	MOT01	0.783	1.656
	MOT02	0.843	2.143
	MOT03	0.887	2.627
	MOT04	0.853	2.312
Points & Badges	PB01	0.834	1.795
	PB02	0.854	1.875
	PB03	0.878	1.799
Perceived Value	PV01	0.856	1.816
	PV02	0.877	2.127
	PV03	0.860	1.886
Rewards & Feedback	RWD01	0.744	1.518
	RWD02	0.851	2.081
	RWD03	0.820	1.748
	RWD04	0.785	1.795
Security	SEC01	0.831	1.558
	SEC02	0.851	1.792
	SEC03	0.853	1.919
Transparency	TRANS01	0.900	1.856

Construct	Item Code	Factor Loading*	VIF
Trust in Blockchain System	TRANS02	0.824	1.751
	TRANS03	0.820	1.706
	TRUST01	0.8620	2.298
	TRUST02	0.891	2.739
	TRUST03	0.816	1.970
	TRUST04	0.811	1.811

4.2.2 Multicollinearity Assessment (VIF)

The variance inflation factor (VIF) was used to measure multicollinearity among the indicators. As per Hair et al. [47], a VIF lower than 3.3 means absence of multicollinearity issues. Anything more conservative suggests value lower than 5.0 is acceptable. All of the VIF values as presented in Table 4 were between 1.29 to 2.74 which are below the limit. Thus, the measurement model was free of multicollinearity and the estimated path coefficients were stable. According to the earlier studies of blockchain and gamification adoption, VIF values are acceptable which means their constructs, such as trust, transparency and motivation, are empirically distinct. In every aspect, the measurement model shows a strong indicator of reliability and multicollinearity problems. Therefore, it can be used for building a structural model. The findings provide empirical evidence supporting the operationalization of blockchain characteristics, gamification mechanisms, and behavioral intention constructs in the Saudi industrial context.

Table 5
Internal Consistency Reliability and Convergent Validity Results

Construct	Cronbach's Alpha	Composite Reliability (pa)	Average Variance Extracted (AVE)
Adoption Intention (AI)	0.833	0.846	0.749
Collaboration (COLLAB)	0.760	0.762	0.678
Decentralization (DECT)	0.729	0.737	0.650
Data Integrity (DI)	0.790	0.800	0.704
Perceived Enjoyment (ENJOY)	0.737	0.749	0.654
Leaderboards (LB)	0.824	0.828	0.740
Motivation (MOT)	0.863	0.866	0.709
Points & Badges (PB)	0.819	0.834	0.732
Perceived Value (PV)	0.831	0.832	0.748
Rewards & Feedback (RWD)	0.813	0.815	0.642
Security (SEC)	0.800	0.802	0.714
Transparency (TRANS)	0.809	0.858	0.720
Trust in Blockchain System (TRUST)	0.867	0.874	0.715

4.2.2 Internal Consistency Reliability and Convergent Validity

Assessing the internal consistency reliability and evaluating convergent validity are both essential for validation of latent constructs in emerging technology adoption models. Consequently, this study evaluated the Cronbach's alpha, composite reliability (pa), and average variance extracted (AVE) to affirm the strength of the measurement model [47], [60]. As shown in Table 5, all constructs have Cronbach's alpha ranging from 0.729 to 0.867, which exceeds the minimum recommended level of 0.70. Hence, all constructs have satisfactory internal consistency reliability [61]. Likewise, the values of composite reliability (pa) varied between 0.737 and 0.874. These results added further verifications to reliability of scales. The AVE values of the constructs used for measuring convergent validity ranged between 0.642 and 0.749, exceeding 0.50. This shows that every construct clarifies more than half of the variance of its respective indicators, which supports sufficient convergent validity [47]. Similar to the findings of earlier blockchain- and gamification-based adoption studies, these findings provide strong evidence for the reliability and validity of the proposed measurement instrument in the

Saudi industrial context. The findings suggest that measurement model meets requisite standards for internal consistency and convergent validity hence allowing the evaluation of subsequent structural model.

4.2.3 Discriminant Validity

To what extent a construct is empirically distinct from other constructs in the model is discriminant validity. In this research a simultaneous use of Heterotrait–Monotrait ratio (HTMT) and Fornell–Larcker approach was applied to assess discriminant validity following Hair et al. [47] recommendations. As one method may not suffice in such complex models for trust, motivation, and value-based constructs. All Latent Constructs HTMT Matrix is given in Table 6. HTMT values must be less than 0.90 (or even less than 0.85 more conservatively) to prove discriminant validity [47]. As indicated in Table 6, the HTMT values are lower than the threshold of 0.90, hence all constructs are empirically distinct. Some construct pairs, like Perceived Value–Motivation and Points & Badges–Trust, display relatively higher HTMT values, yet remain satisfactory. It is theoretically justified to propose an integrated framework, as motivation-driven gamification elements and trust-enhancing blockchain features are theoretically related but not redundant. In gist, the HTMT findings support an acceptable discriminant validity for the measurement model.

Table 6
Heterotrait–Monotrait Ratio (HTMT) Matrix

AI	AI	COLLAB	DECT	DI	ENJOY	LB	MOT	PB	PV	RWD	SEC	TRANS	TRUST
COLLAB	0.892												
DECT	0.734	0.741											
DI	0.757	0.749	0.822										
ENJOY	0.794	0.852	0.647	0.698									
LB	0.78	0.786	0.68	0.757	0.856								
MOT	0.777	0.775	0.73	0.733	0.811	0.765							
PB	0.743	0.744	0.791	0.821	0.743	0.825	0.723						
PV	0.842	0.787	0.745	0.722	0.84	0.703	0.88	0.824					
RWD	0.794	0.84	0.791	0.74	0.803	0.865	0.727	0.785	0.736				
SEC	0.667	0.686	0.699	0.722	0.617	0.708	0.66	0.761	0.613	0.686			
TRANS	0.096	0.064	0.121	0.09	0.076	0.049	0.058	0.106	0.097	0.106	0.105		
TRUST	0.624	0.699	0.857	0.799	0.579	0.701	0.686	0.883	0.748	0.711	0.683	0.12	

The Fornell-Larcker criterion to test is used for discriminant validity. As shown in Table 7, the square root of AVE of each construct (diagonal values) is greater than its respective correlation with other constructs. This suggests that every construct has greater variance with its individual indicators than it does with other latent variables within the model, fulfilling the Fornell–Larcker criterion [62]. Noticeably, the constructs associated with blockchain trust dimensions (security, transparency data integrity and decentralization) and gamification mechanisms (points & badges, leaderboards, rewards and enjoyment) exhibit distinct discriminative boundaries where the trust- motivation- and value-based mechanisms are theoretically distinct from each other in relation to blockchain-enabled AI gamification adoption.

Table 7
Fornell–Larcker Criterion

AI	0.865												
COLLAB	0.708	0.823											
DECT	0.571	0.55	0.806										
DI	0.616	0.584	0.687	0.839									
ENJOY	0.622	0.633	0.481	0.532	0.809								
LB	0.649	0.622	0.524	0.611	0.667	0.86							
MOT	0.665	0.632	0.58	0.609	0.735	0.644	0.842						
PB	0.622	0.592	0.604	0.66	0.585	0.68	0.618	0.856					
PV	0.709	0.626	0.581	0.586	0.664	0.584	0.75	0.68	0.865				
RWD	0.651	0.736	0.604	0.593	0.625	0.708	0.612	0.64	0.606	0.801			
SEC	0.545	0.537	0.531	0.575	0.476	0.577	0.552	0.615	0.504	0.554	0.845		
TRANS	-0.078	-0.042	-0.095	-0.015	-0.05	-0.039	-0.008	-0.085	-0.075	-0.078	-0.07	0.849	
TRUST	0.537	0.57	0.688	0.667	0.474	0.59	0.599	0.734	0.64	0.594	0.573	-0.098	0.846

The results of the HTMT and Fornell–Larcker analyses indicate the presence of discriminant validity for the measurement model proposed. These results confirm that the constructs represent the theoretical dimensions of trust, gamification-driven motivation, perceived value, and adoption intention. This strengthens the robustness of the integrated Trust–Motivation–Value framework.

The measurement model meets the required reliability and validity standards. Thus, the study can now proceed to evaluate the structural model and test the hypothesis.

4.3 Structural Model Assessment and Hypothesis Testing

After establishing the validity of the measurement model and establish reliability of the measurement model, the structural model was assessed using SmartPLS 4 to test the hypothesis among the study constructs. In line with [61], the evaluation of the structural model emphasizes path coefficients (β), t-values, p-values, the coefficient of determination (R^2), and effect size (f^2). A total of 5,000-re samples bootstrapping process was used to determine the significance of the hypothesized paths. The R squared value indicates how well a model explains the data According to statistics in Table 8, Adoption Intention is predicted with 50.3% variance, Motivation 62.1%, Perceived Value 61.9%, and Trust 57.3%, respectively. As stated by Hair et al. [47], when R^2 value is above 0.50 means it is a moderate to substantial predictive accuracy in most behavioral and technology adoption studies. The research illustrates that the integrated Trust–Motivation–Value framework provides a robust explanation of blockchain-enabled AI-based gamification adoption.

Table 8
Structural Model Predictive Accuracy (R^2)

Endogenous Construct	R^2	Adjusted R^2
Adoption Intention (AI)	0.503	0.501
Motivation (MOT)	0.621	0.614
Perceived Value (PV)	0.619	0.616
Trust (TRUST)	0.573	0.566

To determine how an exogenous construct contributes to its corresponding endogenous variable, the effect sizes (f^2) were analyzed. The Results revealed that several relationships exhibit medium to large effect sizes, most notably Motivation > Perceived Value ($f^2 = 0.551$) and Perceived Value > Adoption Intention ($f^2 = 1.011$), indicating strong substantive impact. As shown by their insignificant effect size, the explanatory contribution of theoretical paths, including Rewards & Feedback → Motivation and Transparency → Trust is limited.

4.3.1 Direct Effects: Blockchain Characteristics and Trust

The trust formation mechanisms were tested by investigating the direct impact of the blockchain-related characteristics on trust as shown in Table 9 and Fig. 6. According to the results of the analysis presented in Table 10, it can be seen that decentralization has the highest positive impact on trust ($\beta = 0.375$, $t = 4.683$, $p < 0.001$) followed by data integrity ($\beta = 0.292$, $t = 3.667$, $p < 0.001$) and security ($\beta = 0.203$, $t = 3.614$, $p < 0.001$). These results confirm prior research on blockchain adoption, which emphasise decentralisation and immutability as essential features of trust [63]. On the other hand, transparency has no significant impact on trust ($\beta = -0.044$, $t = 1.032$, $p = 0.302$) and this means it cannot improve trust by itself in AI-blockchain ecosystems. The result may indicate the impact of situational conditions that exist in the Saudi industrial environment, where users tend to prefer system robustness and data protection over informational openness. In general, results partly support the trust-related hypotheses, indicating that trust is a key mediating mechanism in blockchain-enabled systems.

4.3.2 Direct Effects: Gamification Mechanisms and Motivation

Subsequently, the effect of gamification elements on motivation was examined. According to the results, perceived enjoyment dominates the predictors of motivation ($\beta = 0.439$, $t = 6.923$, $p < 0.001$; $f^2 = 0.236$). This underlines the importance of intrinsic motivation in gamified systems endowed with AI. The suitability of motivation benefits from “Points and badges” ($\beta = 0.168$, $p = 0.018$) and collaboration ($\beta = 0.162$, $p = 0.026$). This supports the competence and relatedness dimensions of Self-Determination Theory (Dahri et al, 2025). The effects of leaderboards ($\beta = 0.118$, $p = 0.068$) and rewards and feedback ($\beta = 0.027$, $p = 0.710$) were not significant. The study results indicate that competition and extrinsic rewards are less motivational in professional and industrial learning environments, where autonomy and enjoyment are more relevant.

4.3.3 Direct Effects: Trust, Motivation, Perceived Value, and Adoption Intention

The last set of direct impacts studies the value formation and adoption mechanisms. The effect of motivation on perceived value is significant ($\beta = 0.572$, $t = 9.621$, $p < 0.001$), showing large effect size ($f^2 = 0.551$). Likewise, trust is also found to impact perceived value positively ($\beta = 0.297$, $t = 4.914$, $p < 0.001$) revealing that cognitive trust and affective motivation together impact perceived value. Perceived value has a strong and highly significant positive effect on adoption intention ($\beta = 0.709$, $t = 14.478$, $p < 0.001$), with a very large effect size ($f^2 = 1.011$). This finding shows that perceived value is the most important proximal determinant of adoption intention, which is consistent with value-based extensions of TAM and IS adoption theories.

Table 9
Direct Effects and Hypothesis Testing Results

Path	β	t-value	p-value
COLLAB → MOT	0.162	2.221	0.026
PB → MOT	0.168	2.364	0.018
LB → MOT	0.118	1.825	0.068
ENJOY → MOT	0.439	6.923	0.000
RWD → MOT	0.027	0.373	0.710
DECT → TRUST	0.375	4.683	0.000
DI → TRUST	0.292	3.667	0.000
SEC → TRUST	0.203	3.614	0.000
TRANS → TRUST	-0.044	1.032	0.302
MOT → PV	0.572	9.621	0.000
TRUST → PV	0.297	4.914	0.000
PV → AI	0.709	14.478	0.000

6. Discussion

In this study, we propose and empirically validate an integrated Trust–Motivation–Value framework to explain the adoption of blockchain-enabled AI-based gamification system in Saudi industrial contexts. The findings provide nuanced insights on how blockchain characteristics and gamification mechanisms jointly shape users’ trust, motivation, perceived value and adoption intention, through the

lens of Trust Theory, Self-Determination Theory (SDT), Perceived Value Theory, and technology adoption perspectives. The findings suggest that the adoption of digital ecosystems in advance may not be due to technology features alone. But they are based on users' psychological and value evaluations of these features.

Direct Effects: Blockchain Characteristics and Trust

According to the findings, decentralization, data integrity, and security have a significant positive influence on trust, whereas transparency has no significant effect. This provides theoretical backing to Trust Theory, which asserts that structural assurances and system reliability are the primary antecedents of technology trust [24], [25]. The most potent predictor of trust was decentralization, showing how effective decentralization is in limiting dependence on centralised authorities and in reducing perceived risks, which is a major risk associated with data-intensive AI. Within the Saudi industrial setting, where data protection, cyber security and operational robustness are prioritized in various digital transformation initiatives such as Vision 2030, it seems that users prefer robustness and immutability over visibility. This is consistent with other studies on the blockchain in enterprise and institutional settings, as security and data integrity are deemed more important trust enablers than transparency[64], [65]. The fact that transparency does not play a significant role implies that, unless users have enough knowledge of technology to interpret transparency data flows, transparency cannot become trust. This study contributes to literature by providing insights into the contextual boundary conditions of blockchain trust mechanisms in emerging AI-powered industrial ecosystem [65].

Direct Effects: Gamification Mechanisms and Motivation

As predicted by Self-Determination Theory, perceived enjoyment was the strongest predictor of motivation, with points and badges and collaboration also related to motivation [66]. The presented findings substantiate the perspective that intrinsic motivation serves as a central component in gamified systems in professional yet industrial contexts. The theory postulates that enjoyment reflects a sense of autonomy as well as an intrinsic engagement with what you are doing. In this same theory enjoyment is a fundamental driver of sustainable motivation [67]. This finding is in line with Hamari et al. [15], and Seaborn and Fels [39] whose findings suggest hedonic and experiential components have a stronger impact compared to strictly competitive awards. Rewarding and feedback through leaderboard do not motivate your participants. This is different from certain gamification studies that were undertaken in educational or consumer-based contexts where competition and extrinsic reward have more stress. In industrial settings in Saudi Arabia, employees may see competing rankings and external prizes to be meaningless and even detrimental to collaboration and hierarchy. The new finding adds to earlier gamification studies by showing that motivational affordances are context sensitive. Besides, they suggest that intrinsic and socially supportive mechanisms could be superior to competitive ones in business AI-enabled systems [36].

Direct Effects: Trust, Motivation, Perceived Value, and Adoption Intention

The results additionally confirm that both trust and motivation significantly enhance perceived value which also strongly predicts intention to adopt. This supports Perceived Value Theory that value is the evaluation of a product or service that is dependent on the perceived benefits and perceived cost or risk[68], [69]. Trust in blockchain-enabled AI systems can make them less risky and in turn, motivation can make them more beneficial. These mechanisms jointly provide users with an alternative means to assess system value. The intention to adopt the system is determined strongest by its perceived value at very large effect size. This result supports previous technology adoption studies that consider perceived value to be a proximal antecedent to behavioral intention, especially when it comes to complex and novel technologies [68], [69]. With the organizations in Saudi Arabia rapidly embedding AI and blockchain solutions, the users seem to be more concerned about concrete value outcomes, which include efficiency, reliability, and engagement, rather than technological novelty. This highlights the significance of AI-driven gamification systems that provide discernible and experienced value rather than solely relying on sophisticated features.

Unique Contribution of Blockchain-Enabled AI-Based Gamification

This research has made different contributions to the literature. First, it offers empirical evidence of how the blockchain characteristics give rise to trust among the users of these systems. Further, the all-common model of smartphone examines the convergence of domain adoption theories to explain adopters' behaviour. Besides, the Saudi industrial context provides a new empirical resource from a non-Western and policy-driven digital transformation environment that is not previously studied. The model places perceived value at the nexus between trust, motivation and intention to adopt. As a result, it offers a clear yet insightful view of adoption of next generation digital systems. The insights presented above will not only contribute to theoretical advancement but also offer valuable insights for practitioners. Such practitioners include designers of the system, policymakers, and others seeking to promote sustainable adoption of blockchain-enabled AI gamification solutions in contexts like Saudi Arabia.

7. Conclusion

This study aims to investigate the determinants of adoption of blockchain-enabled AI-based gamification systems through an integrated Trust-Motivation-Value framework. To respond to the rising convergence of blockchain, artificial intelligence and gamification in sophisticated digital ecosystems, we developed and empirically tested a theory-driven model using partial least squares structural equation modelling (PLS-SEM) based on data from the education sectors of Saudi Arabia. The model which integrates Trust Theory, Self-Determination Theory, Perceived Value Theory, and behavioural intention perspectives explains how technological characteristics and gamification mechanisms jointly influence adoption intentions. The findings illustrate blockchain characteristics that relate to trust such as decentralization, data integrity, and security. This establishes trust in blockchain-enabled AI. According to this theory, trust significantly positively impacts perceived value, suggesting that users' trust in the underlying technology is necessary in order to value something positively. On the contrary, transparency did not have an influence on trust meaning visible things do not work unless users are able to understand and make sense of the transparent process in the system. This is more so the case for complicated AI-driven scenarios, where dependence on system robustness and reliability is greater than informational transparency. Study affirmed intrinsic and social oriented mechanisms are primarily responsible for motivation on the gamification side. The findings suggest that motivation is most strongly predicted by perceived enjoyment, followed by points and badges, and collaboration, while leaderboard and rewards and feedback are non-significant. The results correspond with the Self-Determination Theory, which suggests that the importance of autonomy, competence, and relatedness outweighs the competitive or extrinsically based motivational schemes used in professional or industrial settings. Motivation was found to significantly enhance perceived value, highlighting the importance of engagement, pleasure, and motivation in its technology evaluation. According to our findings, perceived value is the strongest factor determining adoption intention, suggesting that blockchain-enabled AI gamification systems are adopted by users when users perceive them to offer clear functional, psychological and experiential benefits. The findings imply that adoption does not occur due to a single technological feature. Rather, adoption is an interconnected process whereby trust and motivation create perceptions of value which lead to behavioural intention. Through an empirical validation of this integrated framework, this study will advance the understanding of how next-generation digital technologies can be sustainably adopted in a complex organizational setting.

8. Limitations and Future Research Directions

This study has limitations worth acknowledging. Initially, the empirical evidence was collected from education sectors in Saudi Arabia, which restricts generalizability to national, cultural or other institutional settings. Saudi Arabia is a special environment because of the rapid adoption of nascent technologies and strong state support for digital transformation. Future research should allow for testing the model in another region or across countries to determine the robustness and validity of the proposed framework. Furthermore, the study utilized cross-sectional survey design, which does not provide a causal inference nor tracks the change in perception over time. The adoption of blockchain-enabled AI gamification is likely to mature with user experience and organizational policy maturation. Mixed – method perspectives such as systems usage data or interviews along with longitudinal research designs could inform how trust, motivation and perceived value develop over time in the course of adoption. Thirdly, although the study examined adoption intention as the main outcome, it did not investigate form-post adoption behaviours that include continued usage, system satisfaction, performance outcomes, and organizational impact. Future research may apply this model to facilitate continuance intention, actual usage behavior, productivity outcomes, or sustainability performance indicators. Besides, other psychological and contextual moderators, such as digital literacy, AI anxiety, culture, ethics and risk perception, can also be studied for better adoption.

9. Implications for Theory, Practice, Policy, and Sustainability

- The present study holds various implications in theory. The initial contribution refers to research on technology adoption, especially by proposing an integrated Trust – Motivation – Value framework that encompasses technological, psychological and evaluative mechanisms. This study shows that, unlike the intention-based models that emphasize perceived usefulness and ease of use, the adoption of blockchain-enabled AI gamification relies on deeper cognitive and affective assessments involving trust and intrinsic motivation. The study builds on Trust Theory and Self-Determination Theory in the context of AI-powered blockchain applications and places the perceived value as a crucial explanatory tool. The perspective enhances the evolving theoretical discourse on emergent digital technologies and it offers a parsimonious yet integrative model for complex adoption contexts.
- The practical findings can aid organizations and technology developers in their efforts. The design of a Blockchain-enabled AI Gamified platform should focus on developing trust and not clarity. A highly secured decentralized system with data integrity. Gamification strategies should be focused on fun meaningful achievement recognition and collaboration rather than intense

competition and reward. When systems are designed to correspond with users' psychological needs and trust expectations, their perceived value is enhanced, and adoption is credible.

- At the level of policy, the findings indicate a "need for the existence of regulatory frameworks or institutional guidelines that enhance trust in blockchain and AI". Policymakers in Saudi Arabia and other digitally transforming economies should promote standards around data security, ethical use of AI and blockchain governance to reduce uncertainty and build confidence among users. Having clear policies can also encourage organizations to adopt gamified AI solutions in a responsible and value-driven manner. The study has important implications for sustainability. Blockchain-enhanced AI gamification is a sustainable digital innovation that fosters long-lasting user engagement through transparent and secure systems. When people are motivated from within, they build trust which helps in minimizing resistance towards technology change. Further, it supports continuous learning, innovation, and performance improvement. With this in mind, the blockchain-enabled AI gamification is a setup for diverse business fields, along with the tech setup. As such, the research helps to enhance the sustainability dialogue through adopting new sophisticated digital technologies in a manner which maintains a balance between efficiency, trust, and human-value generation.

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Figures

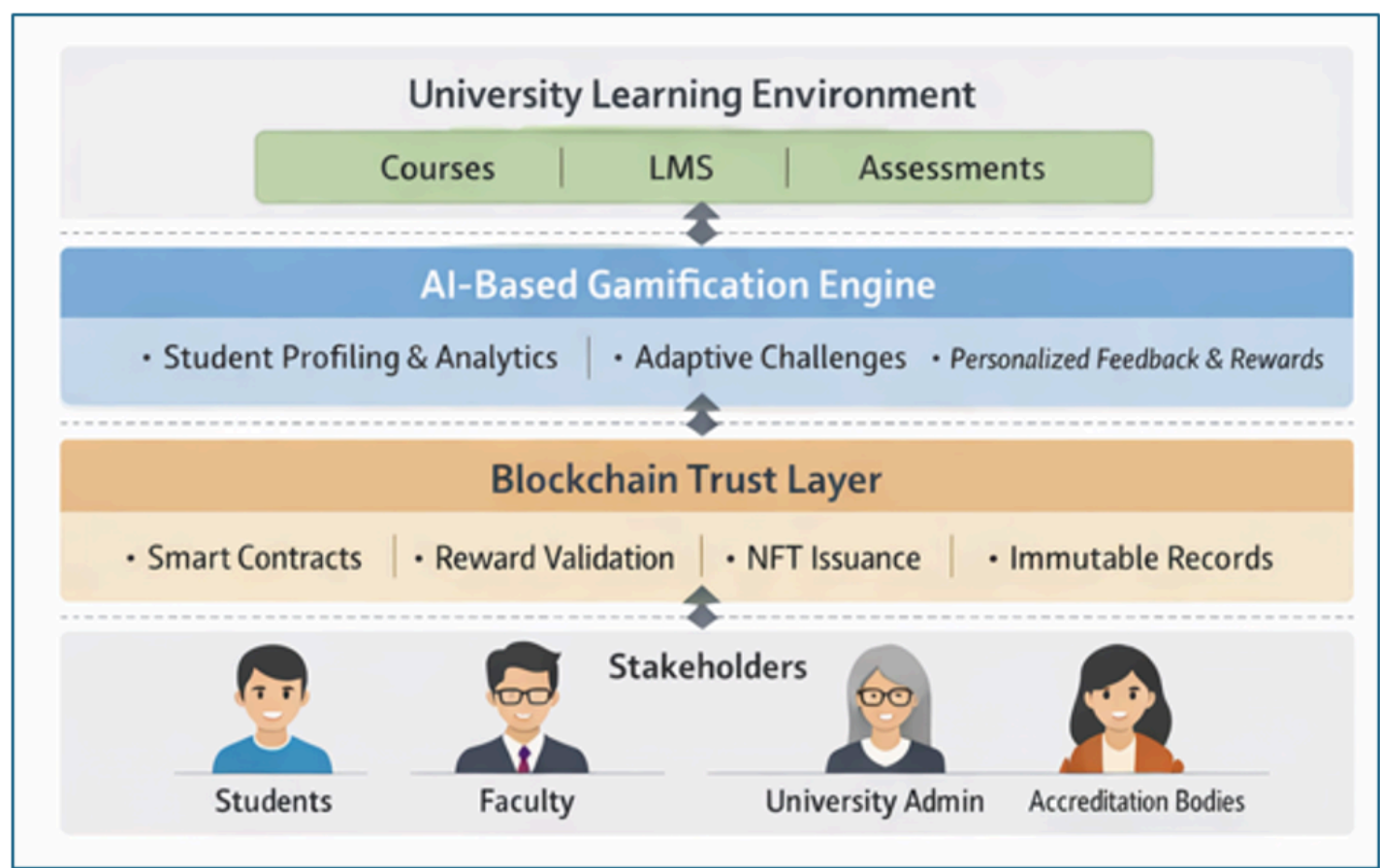


Figure 1 presents the proposed Architecture of Blockchain-Enabled AI-Based Gamification in Education, illustrating how AI modules (adaptive learning, analytics, and feedback engines) interact with gamification components (points, badges, leaderboards, and rewards), while blockchain ensures decentralized storage, immutability, smart-contract-based reward validation, and credential verification.

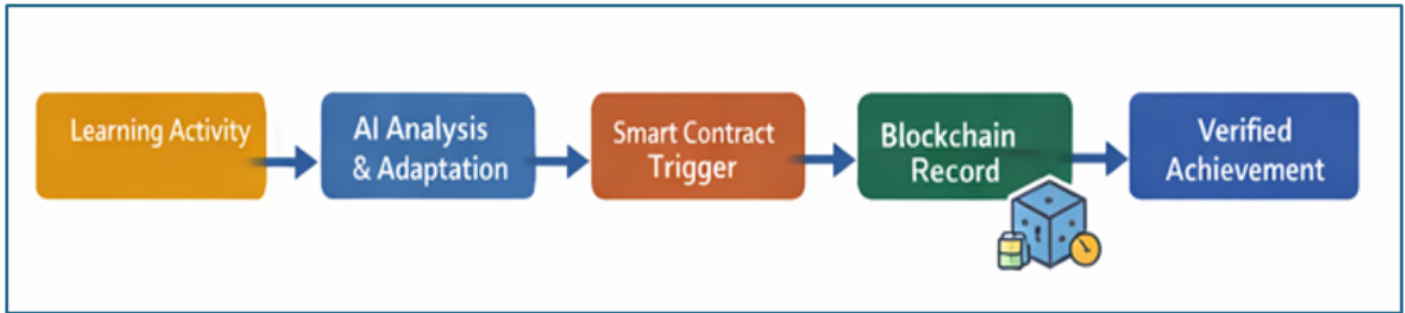


Figure 2

Operational Flow of AI-Based Gamification Supported by Blockchain

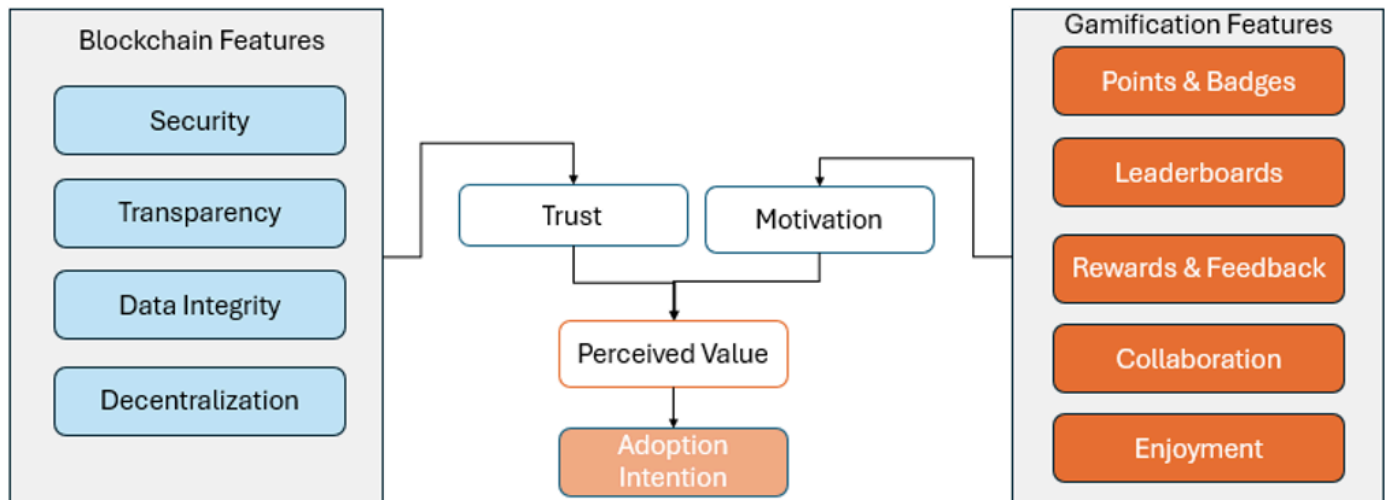


Figure 3

Proposed Research model: This figure presents illustrating the relationships among blockchain features and gamification features. Trust and motivation act as mediating constructs influencing perceived value, which in turn determines users' adoption intention toward blockchain-enabled AI-based gamified education.

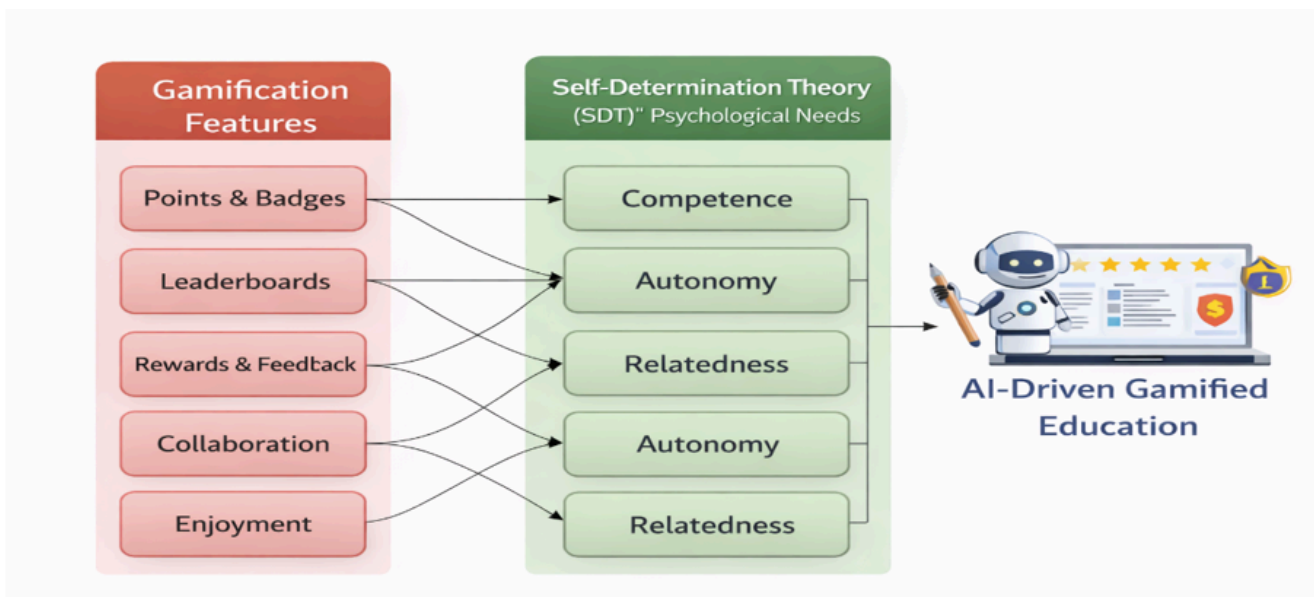


Figure 4

Gamification features and SDT theory relationships: *This figure depicts the conceptual mapping between gamification features and the core psychological needs of Self-Determination Theory (SDT)*

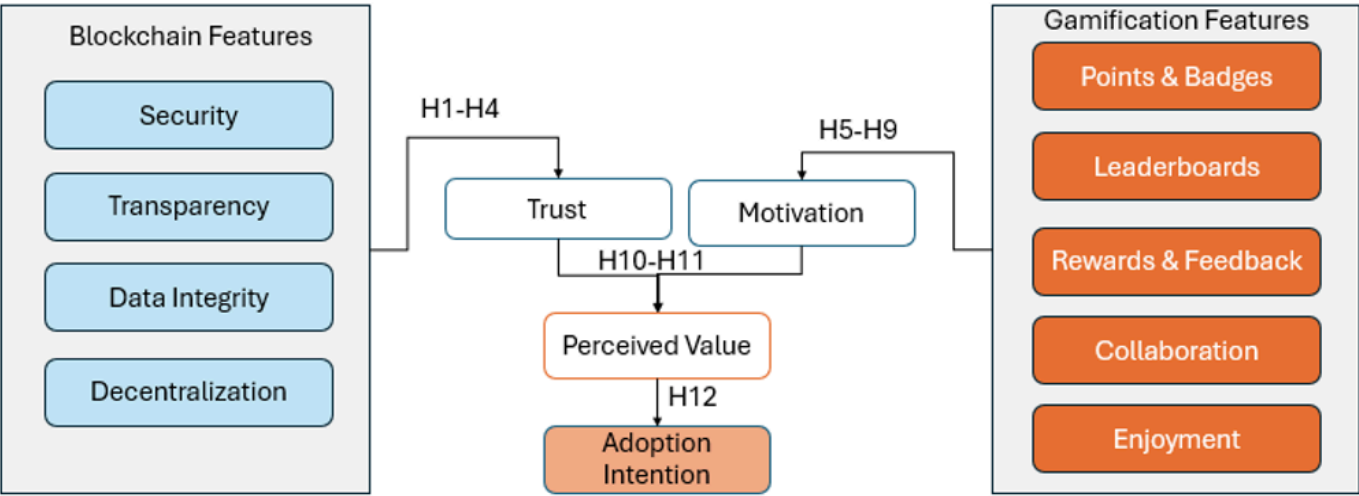


Figure 5

Proposed Hypothesized relationships

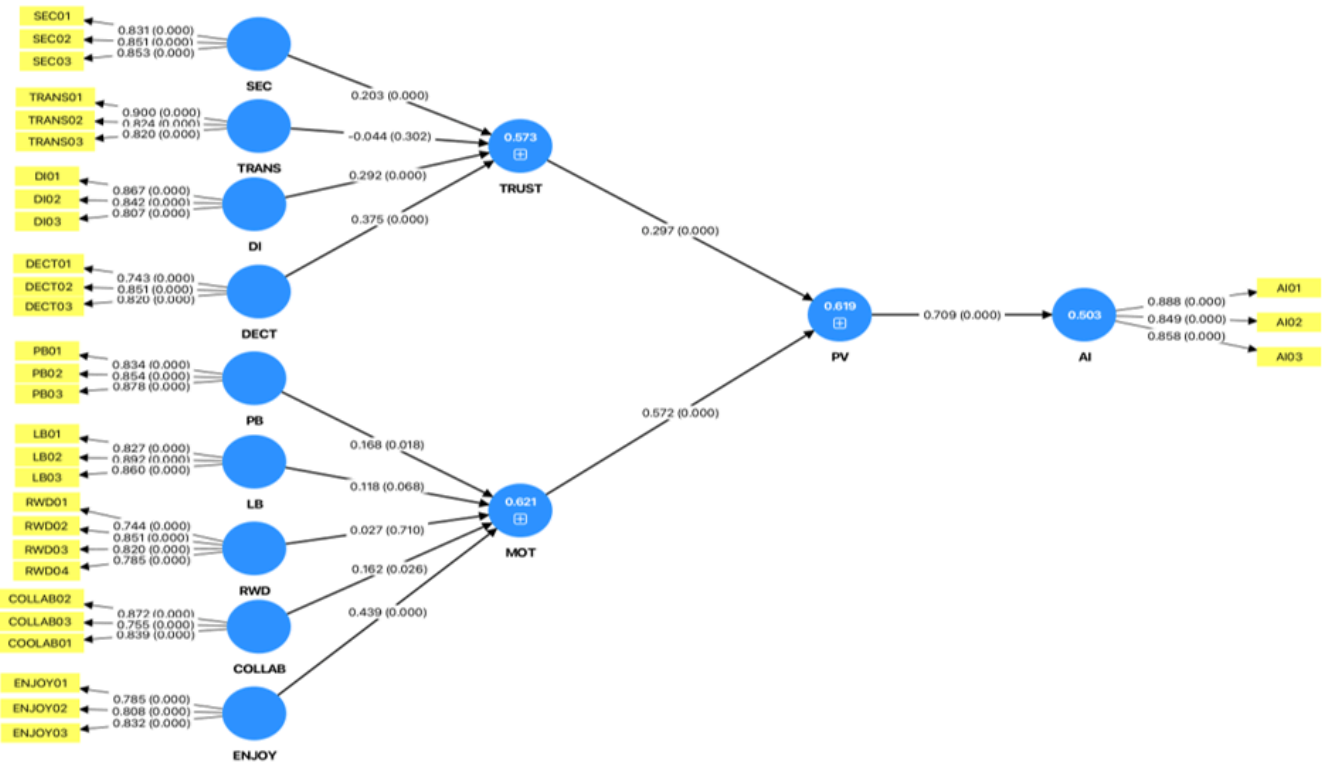


Figure 6

Structural model results of hypothesis