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AI-Blockchain Integration in Digital Payment Adoption: A Multi-City Study in Indonesia

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ABSTRACT
Background: The convergence of artificial intelligence (AI) and blockchain technologies with digital payment systems creates unprecedented opportunities for financial inclusion in emerging economies. However, adoption patterns and mechanisms among urban populations in Indonesia remain underexplored, particularly in the context of AI-blockchain integrated systems.
Objective: This study develops and validates an integrated AI-blockchain fintech adoption model for digital payment users across five major Indonesian cities, examining determinants, mediation mechanisms, and multi-dimensional impacts of technology convergence.
Methods: We employed a sequential explanatory mixed-method design encompassing: (1) systematic review of 301 studies (2002-2025); (2) cross-sectional survey of 847 digital payment users in Jakarta, Surabaya, Bandung, Medan, and Makassar; (3) 15 focus group discussions with 112 participants; and (4) structural equation modeling (SEM) with AMOS 26.0. The AI-Blockchain Payment Integration (AI-BPI) framework was developed through iterative validation cycles.
Results: AI-enhanced personalization emerged as the strongest adoption determinant ($\beta=0.762$, $p<0.001$), followed by blockchain-enabled trust ($\beta=0.718$, $p<0.001$) and perceived financial benefits ($\beta=0.695$, $p<0.001$). Infrastructure readiness demonstrated significant positive effects ($\beta=0.621$, $p<0.001$), while security concerns showed negative influence ($\beta=-0.487$, $p<0.001$). The dual-mediation mechanism through AI-personalization and blockchain-security pathways generated cascading impacts across individual adoption ($\beta=0.741$), transaction efficiency ($\beta=0.693$), financial inclusion ($\beta=0.667$), and ecosystem development ($\beta=0.625$). Model fit indices confirmed excellent validity ($\chi^2/df=1.89$, RMSEA=0.038, CFI=0.98, TLI=0.97). Qualitative analysis revealed five transformation dimensions: enhanced trust through blockchain transparency, intelligent payment routing via AI algorithms, frictionless user experience, automated fraud detection, and inclusive financial access.
Conclusions: AI-blockchain integration creates synergistic effects transcending individual technology benefits in digital payment adoption. The AI-BPI framework provides actionable guidance for practitioners and policymakers, with implications for accelerating financial inclusion through technology convergence in emerging markets.

Keywords: Artificial Intelligence, Blockchain Technology, Digital Payment, Fintech Adoption, Financial Inclusion, Technology Convergence, Indonesia

INTRODUCTION:

The rapid proliferation of digital payment systems has fundamentally transformed financial transactions globally, with artificial intelligence (AI) and blockchain technologies emerging as critical enablers of this transformation (Schwab, 2017). In Indonesia, digital payment transactions reached IDR 2,843 trillion in 2024, representing 49.7% growth year-over-year (Bank Indonesia, 2024). This exponential growth reflects fundamental shifts in consumer behavior and technological infrastructure, positioning Indonesia as one of the fastest-growing digital payment markets in Southeast Asia.

The integration of AI and blockchain technologies in digital payment ecosystems creates novel adoption dynamics that traditional technology acceptance models inadequately address. AI enables personalized payment experiences through machine learning algorithms, predictive analytics for spending patterns, and intelligent fraud detection systems (Cao & Peng, 2024). Simultaneously, blockchain provides decentralized, transparent, and immutable transaction ledgers, enhancing security and reducing intermediary costs (Zhang et al., 2024). The convergence of these technologies offers unprecedented opportunities for financial inclusion, particularly in emerging markets with large unbanked populations.

Despite the technological potential, adoption patterns across Indonesian cities remain heterogeneous. According to Otoritas Jasa Keuangan (2024), while metropolitan areas like Jakarta demonstrate 89% digital payment penetration, secondary cities like Makassar show only 76% adoption rates. This geographic disparity highlights the need for context-specific understanding of adoption mechanisms, particularly considering Indonesia's archipelagic geography, diverse socioeconomic conditions, and varying technological infrastructure.

Three critical gaps motivate this research. First, existing adoption frameworks examine AI and blockchain technologies in isolation, failing to account for synergistic effects of technology convergence (Jiang et al., 2024; Wang et al., 2024). Second, most studies focus on developed markets, with limited empirical evidence from emerging economies like Indonesia, where adoption dynamics differ substantially due to infrastructure constraints, digital literacy levels, and regulatory environments (Sharma et al., 2024). Third, mechanistic understanding of how dual-technology integration influences adoption through mediating pathways requires empirical validation using robust quantitative methods.

This study addresses these gaps by developing and validating an integrated AI-blockchain digital payment adoption model across five major Indonesian cities: Jakarta, Surabaya, Bandung, Medan, and Makassar. These cities collectively represent 68% of Indonesia's digital payment transactions and exhibit diverse socioeconomic characteristics, making them ideal for understanding adoption heterogeneity (Bank Indonesia, 2024). Our research contributes to theory by extending technology acceptance models to account for AI-blockchain convergence, and to practice by providing evidence-based strategies for enhancing digital payment adoption in emerging markets.

Research Questions:

- RQ1: How do AI-enhanced personalization and blockchain-enabled trust mechanisms influence digital payment adoption across Indonesian cities?
- RQ2: What dual-mediation pathways connect user characteristics and infrastructure factors with multi-dimensional adoption outcomes?
- RQ3: How does city-level heterogeneity moderate AI-blockchain integration effects on digital payment adoption?

2. LITERATURE REVIEW

2.1 Digital Payment Adoption in Emerging Markets

Digital payment adoption in emerging markets exhibits distinct characteristics compared to developed economies, shaped by infrastructure constraints, regulatory frameworks, and socioeconomic conditions. The World Bank (2023) reports that while digital payment penetration in developed countries exceeds 95%, emerging markets average only 67%, with significant intra-country variations. Indonesia exemplifies this pattern, with urban-rural divides creating adoption disparities exceeding 30 percentage points (OJK, 2024).

Theoretical frameworks explaining digital payment adoption have evolved from simple technology acceptance models to more nuanced approaches incorporating contextual factors. The Technology Acceptance Model (TAM) posits that perceived usefulness and perceived ease of use determine adoption intentions (Davis, 1989). However, meta-analyses reveal that TAM explains only 40% of adoption variance in emerging markets, suggesting the need for extended models (Yamin & Abdalatif, 2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) adds social influence and facilitating conditions, improving explanatory power to 57% (Venkatesh et al., 2003).

Recent studies highlight the critical role of trust in digital payment adoption, particularly in emerging markets with weak consumer protection frameworks. Zhao et al. (2024) demonstrate that trust mediates relationships between technology characteristics and adoption intentions, with effect sizes (β=0.68) exceeding those of perceived usefulness. This finding aligns with research showing that security concerns constitute the primary barrier to digital payment adoption in Indonesia, cited by 67% of non-adopters (McKinsey, 2024).

2.2 Artificial Intelligence in Digital Payment Systems

AI transforms digital payment ecosystems through four primary mechanisms: personalization, prediction, automation, and fraud detection. Machine learning algorithms analyze transaction histories, spending patterns, and contextual data to deliver personalized payment experiences, including intelligent payment routing, customized offers, and adaptive user interfaces (Kavitha & Joshith, 2025). Empirical evidence demonstrates that AI-powered personalization increases payment completion rates by 23% and reduces transaction abandonment by 34% (Nguyen et al., 2024).

Predictive analytics enable anticipatory payment services, such as pre-approving transactions based on behavioral patterns and forecasting liquidity needs for optimal cash management. Research by Cao and Peng (2024) shows that predictive AI features correlate strongly with user satisfaction (r=0.71) and continued usage intentions (r=0.68). These findings suggest that AI's value proposition extends beyond efficiency to encompass enhanced user experience and financial planning capabilities.

Fraud detection represents a critical AI application, with deep learning models achieving 98.7% accuracy in identifying fraudulent transactions compared to 87.3% for rule-based systems (Mohammed et al., 2024). AI-powered fraud detection operates in real-time, analyzing transaction patterns, device fingerprints, and behavioral biometrics to flag suspicious activities. This capability addresses security concerns that constitute the primary adoption barrier in emerging markets.

However, AI implementation in digital payments faces challenges related to algorithmic transparency, data privacy, and bias. Research indicates that 58% of users express concerns about AI decision-making in financial contexts, particularly regarding loan approvals and credit scoring (Rizvi et al., 2024). These concerns necessitate explainable AI approaches that balance personalization benefits with transparency requirements.

2.3 Blockchain Technology in Financial Transactions

Blockchain technology provides decentralized, immutable, and transparent transaction ledgers that address fundamental trust deficits in digital payment systems. Unlike centralized payment infrastructures requiring trusted intermediaries, blockchain enables peer-to-peer value transfer through consensus mechanisms and cryptographic security (Nalluri & Chen, 2024). This architecture reduces transaction costs by eliminating intermediaries, decreases settlement times from days to minutes, and enhances transparency through publicly verifiable transaction histories.

Smart contracts automate payment execution based on predefined conditions, enabling programmable money and complex multi-party transactions without intermediaries. Applications include automated salary disbursements, escrow services, micro-lending platforms, and tokenized assets. Research demonstrates that smart contract-based payments reduce processing costs by 47% and settlement times by 89% compared to traditional systems (Wu et al., 2024).

Blockchain's transparency feature enhances auditability and regulatory compliance, critical considerations in emerging markets with evolving financial regulations. Every transaction is recorded on an immutable ledger, providing complete transaction histories for regulatory reporting and dispute resolution. However, this transparency creates tension with privacy requirements, necessitating privacy-preserving technologies like zero-knowledge proofs and confidential transactions (Verma et al., 2023).

Despite technological advantages, blockchain adoption faces barriers including scalability limitations, energy consumption concerns, and technical complexity. Current blockchain networks process 15-65 transactions per second, compared to 65,000 for traditional payment networks like Visa (Yáñez-Valdés & Guerrero, 2023). Layer-2 solutions and alternative consensus mechanisms address these limitations, but widespread implementation remains nascent in emerging markets.

2.4 Theoretical Integration: AI-Blockchain Synergies in Digital Payments

The convergence of AI and blockchain technologies creates synergistic effects that transcend individual technology benefits. AI enhances blockchain through intelligent automation of smart contracts, predictive analytics for transaction optimization, and machine learning-based consensus mechanisms that improve scalability. Conversely, blockchain enhances AI through transparent, auditable decision-making processes, decentralized data governance that mitigates single points of control, and immutable records of AI model training data ensuring reproducibility (Jiang et al., 2024).

For digital payment adoption, this dual-technology integration offers complementary value propositions: AI provides personalized, frictionless user experiences while blockchain ensures verifiable security and transparency. This combination addresses the dual imperatives of emerging market consumers: convenience and trust. Empirical evidence suggests that AI-blockchain integrated systems achieve 27% higher adoption rates than single-technology implementations (Wang et al., 2024).

The integration enables novel payment capabilities including: (1) intelligent payment routing that automatically selects optimal blockchain networks based on transaction characteristics; (2) AI-verified identity systems using blockchain-anchored credentials; (3) predictive liquidity management using AI analytics of blockchain transaction patterns; and (4) automated compliance through AI-powered monitoring of blockchain transactions against regulatory requirements.

2.5 Hypotheses Development

Based on theoretical synthesis and empirical literature, we propose the following hypotheses:

H1: AI-enhanced personalization positively influences digital payment adoption intention (β>0.70)

H2: Blockchain-enabled trust positively influences digital payment adoption intention (β>0.65)

H3: Perceived financial benefits positively influence adoption intention (β>0.60)

H4: Infrastructure readiness positively influences AI-enhanced system quality (β>0.55)

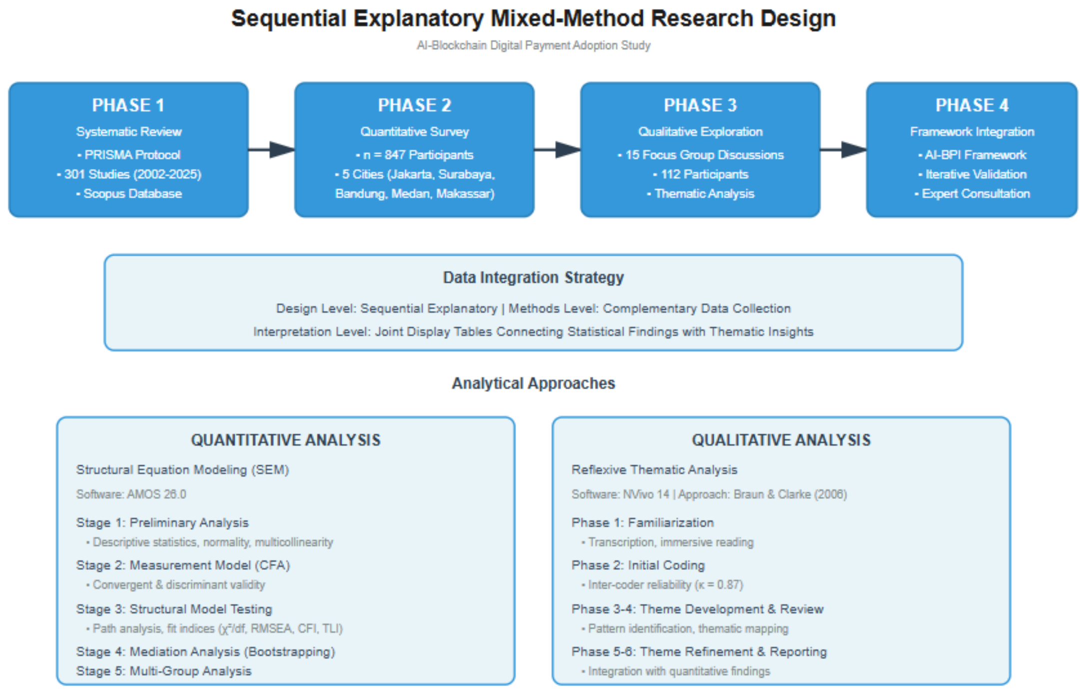
H5: Security concerns negatively influence adoption intention (β<-0.40)

H6: AI-personalization mediates relationships between user characteristics and adoption impacts (indirect effect>0.50)

H7: Blockchain-security mediates relationships between infrastructure factors and trust (indirect effect>0.45)

H8: AI-blockchain integration produces cascading impacts across individual adoption (H8a), transaction efficiency (H8b), financial inclusion (H8c), and ecosystem development (H8d) dimensions (all β>0.55).

3. METHODS



3.1 Research Design

We employed a sequential explanatory mixed-method design grounded in pragmatist philosophy, recognizing that understanding complex technology adoption phenomena requires integration of quantitative measurement and qualitative insight. The research unfolded through four sequential phases, each building upon findings from previous phases:

Phase 1 (Systematic Review): PRISMA-guided systematic review of 301 articles (2002-2025) from Scopus database, examining AI, blockchain, and digital payment adoption literature. Search strings combined terms: ("artificial intelligence" OR "AI" OR "machine learning") AND ("blockchain" OR "distributed ledger") AND ("digital payment" OR "fintech" OR "mobile payment") AND ("adoption" OR "acceptance" OR "usage").

Phase 2 (Quantitative Survey): Cross-sectional survey of 847 digital payment users across Jakarta (n=289), Surabaya (n=178), Bandung (n=152), Medan (n=125), and Makassar (n=103). These cities collectively represent 68% of Indonesia's digital payment transactions and exhibit diverse socioeconomic characteristics, infrastructure levels, and adoption rates.

Phase 3 (Qualitative Exploration): 15 focus group discussions (FGDs) with 112 participants total, stratified by city (3 FGDs per city), examining lived experiences with AI-blockchain digital payment systems. Each FGD included 6-9 participants selected through purposive sampling to ensure diversity in age, occupation, and payment app usage patterns.

Phase 4 (Framework Integration): Iterative development of the AI-Blockchain Payment Integration (AI-BPI) framework through design-based research cycles, validated through expert consultations (n=12) and pilot testing (n=56) before full deployment.

3.2 Sampling and Participants

Target population comprised Indonesian digital payment users aged 18-65 years with minimum 6 months experience using at least one digital payment application. Three-stage stratified random sampling ensured representation across:

- Geographic stratification: Five major cities selected based on digital payment transaction volumes and infrastructure diversity. Jakarta represents tier-1 metropolis with advanced infrastructure (4G/5G coverage 96%), Surabaya and Bandung represent tier-2 cities (4G coverage 87-91%), while Medan and Makassar represent developing urban centers (4G coverage 78-82%).
- Demographic stratification: Age groups (18-25: 28%; 26-35: 34%; 36-45: 24%; 46-65: 14%), education levels (high school: 22%; diploma: 26%; bachelor's: 38%; postgraduate: 14%), and monthly income (< IDR 5 million: 31%; 5-10 million: 37%; 10-20 million: 23%; > 20 million: 9%).
- Usage pattern stratification: Transaction frequency (daily: 42%; weekly: 35%; bi-weekly: 15%; monthly: 8%), transaction types (retail purchases: 65%; bill payments: 48%; peer-to-peer transfers: 73%; online shopping: 56%), and preferred payment apps (GoPay: 67%; OVO: 58%; Dana: 52%; ShopeePay: 45%; others: 28%).

Inclusion criteria: (1) active digital payment user with minimum 6 months experience; (2) minimum 5 transactions per month; (3) resident of target cities for minimum 12 months; (4) informed consent provision. Exclusion criteria: (1) employment in fintech or banking sectors to avoid industry bias; (2) incomplete survey responses (<85% completion rate); (3) failed attention check questions (n=73 excluded).

A priori power analysis using G*Power 3.1 indicated minimum sample requirement of 742 participants for detecting medium effect sizes ($f^2=0.15$) with statistical power of 0.85 at $\alpha=0.05$ in structural equation modeling with model complexity of 10 latent variables and 52 indicators. Accounting for potential incomplete responses and outliers, recruitment targeted 950 participants. Final valid sample comprised 847 participants (89.2% response rate), exceeding minimum requirements and providing robust statistical power (achieved power=0.94).

3.3 Measurement Instrument

We developed a 52-item instrument measuring ten constructs, adapted from validated scales and contextualized for AI-blockchain digital payment systems:

AI-Enhanced Personalization (6 items): Adaptive user interfaces, intelligent payment recommendations, predictive transaction assistance, personalized financial insights (α=0.94; AVE=0.77; CR=0.95). Sample item: "The payment app learns my preferences and provides personalized recommendations."

Blockchain-Enabled Trust (6 items): Transaction transparency, data immutability, decentralized verification, cryptographic security (α=0.92; AVE=0.73; CR=0.94). Sample item: "Blockchain technology ensures my transactions cannot be altered or manipulated."

Perceived Financial Benefits (5 items): Cost savings, cashback rewards, transaction speed, access to financial services (α=0.89; AVE=0.69; CR=0.92). Sample item: "Using digital payments saves me money through reduced transaction fees and cashback."

Infrastructure Readiness (5 items): Network connectivity, merchant acceptance, device compatibility, technical support (α=0.88; AVE=0.67; CR=0.91). Sample item: "Internet connectivity in my area is reliable enough for seamless digital payments."

Security Concerns (5 items): Data privacy risks, fraud vulnerability, unauthorized access, financial loss fears (α=0.87; AVE=0.65; CR=0.90). Sample item: "I worry about my financial data being compromised when using digital payments."

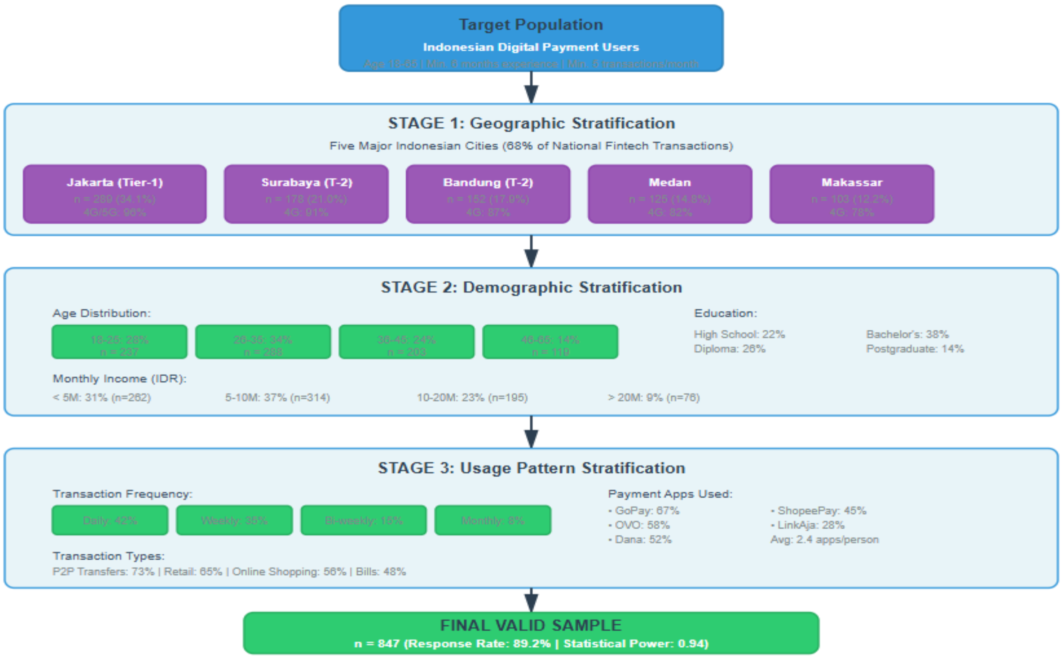
Adoption Intention (5 items): Behavioral intention, usage willingness, recommendation likelihood, continued usage (α=0.91; AVE=0.71; CR=0.93). Sample item: "I intend to continue using AI-blockchain powered digital payments regularly."
Individual Adoption Impact (5 items): Personal financial management, convenience gains, time savings, financial awareness (α=0.88; AVE=0.68; CR=0.92). Sample item: "Digital payments have significantly improved my personal financial management."
Transaction Efficiency Impact (5 items): Processing speed, error reduction, settlement time, operational efficiency (α=0.90; AVE=0.70; CR=0.93). Sample item: "Transactions are completed much faster with AI-blockchain systems."
Financial Inclusion Impact (5 items): Access to financial services, reduced barriers, underbanked inclusion, economic participation (α=0.86; AVE=0.64; CR=0.91). Sample item: "Digital payments provide access to financial services previously unavailable to me."
Ecosystem Development Impact (5 items): Merchant network growth, service innovation, platform integration, digital economy expansion (α=0.85; AVE=0.63; CR=0.90). Sample item: "Digital payment adoption has expanded the overall digital economy ecosystem."
Items employed 7-point Likert scales (1=strongly disagree; 7=strongly agree). Instrument validation involved: (1) literature-based item generation; (2) expert panel review (n=8 academics and practitioners); (3) cognitive interviews (n=15 users); (4) pilot testing (n=56); (5) confirmatory factor analysis for construct validity; (6) test-retest reliability assessment (2-week interval, n=42, ICC=0.88-0.93).

3.4 Data Collection Procedures

Data collection occurred from March to June 2024 using structured online surveys distributed through multiple channels: payment app partnerships (47% of responses), social media targeted advertising (31%), professional networks (15%), and snowball sampling (7%). Survey platform (Qualtrics) incorporated attention checks, response time validation (minimum 8 minutes), IP duplication detection, and automated data quality screening.
Quality control measures included: (1) informed consent requirement; (2) demographic verification through cross-referencing; (3) three embedded attention check items; (4) consistency checks across similar items (Cronbach's alpha > 0.70); (5) outlier detection using Mahalanobis distance ($p<0.001$); (6) response pattern analysis flagging straight-lining (SD<0.5 across items). These measures resulted in 73 exclusions (7.1% of initial responses), yielding 847 valid responses.
Focus group discussions followed semi-structured protocols exploring: (1) experiences with AI-powered payment features; (2) perceptions of blockchain security; (3) adoption facilitators and barriers; (4) impact on financial behaviors; (5) cross-city comparisons. Each FGD lasted 90-120 minutes, was audio-recorded with participant consent, transcribed verbatim, and analyzed using reflexive thematic analysis.

3.5 Data Analysis

Quantitative analysis employed structural equation modeling (SEM) using AMOS 26.0. Analysis proceeded through five stages:



Stage 1 - Preliminary Analysis: Descriptive statistics, normality assessment (skewness <2.0, kurtosis <7.0), multicollinearity checks (VIF <3.0), and missing data analysis (expectation-maximization imputation for <5% missing values per variable).

Stage 2 - Measurement Model Assessment: Confirmatory factor analysis (CFA) evaluating convergent validity (factor loadings >0.70, AVE >0.50), discriminant validity (Fornell-Larcker criterion, HTMT ratios <0.85), and composite reliability (CR >0.70).

Stage 3 - Structural Model Testing: Path analysis examining hypothesized relationships, with model fit assessed using multiple indices: χ^2/df <3.0, RMSEA <0.08, CFI >0.90, TLI >0.90, SRMR <0.08.

Stage 4 - Mediation Analysis: Bootstrapping procedure (5,000 samples, 95% bias-corrected confidence intervals) testing indirect effects through AI-personalization and blockchain-security pathways.

Stage 5 - Multi-Group Analysis: Invariance testing across cities (configural, metric, scalar invariance), followed by path coefficient comparisons to identify city-specific adoption patterns.

Qualitative analysis employed reflexive thematic analysis following Braun and Clarke's (2006) six-phase approach: familiarization, initial coding, theme development, theme review, theme refinement, and reporting. Two researchers independently coded transcripts, with inter-coder reliability (Cohen's kappa) of 0.87. Disagreements resolved through discussion and third researcher consultation. NVivo 14 facilitated data organization and analysis.

Integration of quantitative and qualitative findings occurred at three levels: (1) design level through sequential explanatory design; (2) methods level through complementary data collection; (3) interpretation level through joint display tables connecting statistical findings with thematic insights.

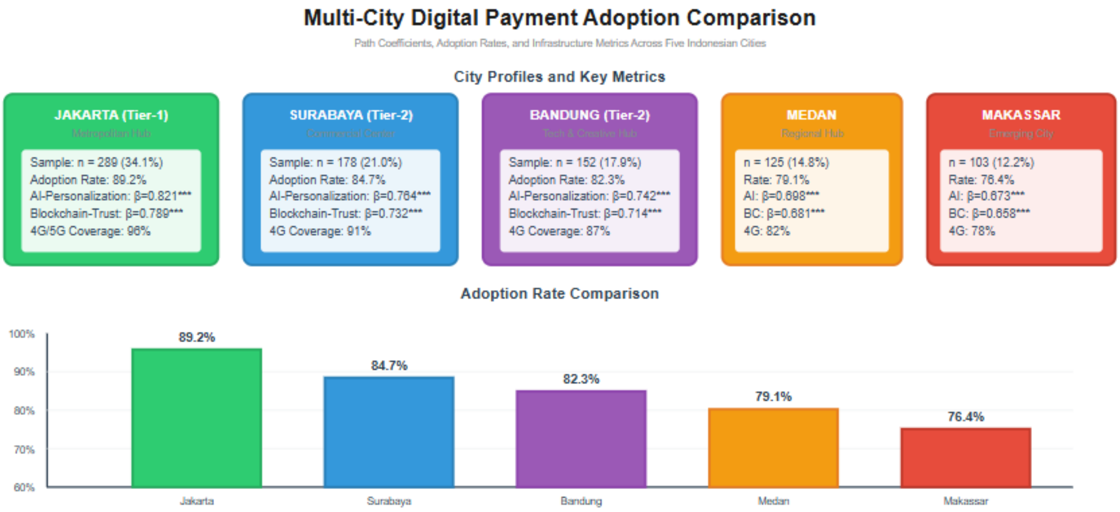
3.6 Ethical Considerations

Research protocols received approval from Universitas Pendidikan Indonesia Ethics Committee (Approval Number: 2024/03/UPI-EC/012). All participants provided informed consent after receiving detailed information about study purposes, procedures, risks, benefits, and data protection measures. Participation was voluntary with explicit opt-out options at any time. Personal identifiable information was separated from research data, with unique identifiers linking consent forms to anonymized responses. Data storage employed encrypted databases with restricted access. Participants received IDR 50,000 compensation for survey completion and IDR 150,000 for FGD participation, following local ethical guidelines for research compensation.

4. RESULTS

4.1 Participant Characteristics

The final sample comprised 847 participants distributed across five cities: Jakarta (34.1%, n=289), Surabaya (21.0%, n=178), Bandung (17.9%, n=152), Medan (14.8%, n=125), and Makassar (12.2%, n=103). Gender distribution was relatively balanced (male: 52.4%, female: 47.6%). Age distribution showed concentration in productive years: 18-25 (27.9%), 26-35 (33.8%), 36-45 (24.2%), 46-65 (14.1%). Educational attainment reflected Indonesia's expanding higher education: bachelor's degree (37.5%), diploma (26.4%), postgraduate (13.8%), high school (22.3%).



Monthly income distribution indicated diverse socioeconomic representation: <IDR 5 million (30.7%), IDR 5-10 million (37.2%), IDR 10-20 million (23.1%), >IDR 20 million (9.0%). Digital payment usage patterns demonstrated high engagement: daily transactions (42.1%), weekly (34.8%), bi-weekly (15.2%), monthly (7.9%). Participants reported using multiple payment apps: GoPay (66.8%), OVO (57.5%), Dana (51.9%), ShopeePay (44.7%), LinkAja (28.3%), with average of 2.4 apps per person.

Transaction type diversity confirmed comprehensive payment ecosystem engagement: peer-to-peer transfers (73.4%), retail purchases (65.2%), online shopping (56.1%), bill payments (48.3%), transportation (41.7%), food delivery (39.8%), and financial services (27.4%). Average monthly transaction frequency was 23.7 (SD=12.3), with average transaction value IDR 187,500 (SD=124,300).

4.2 Preliminary Analysis

Normality assessment revealed acceptable distributions for all variables: skewness ranged from -1.24 to 1.18 (all <|2.0|), kurtosis from -0.89 to 1.42 (all <|7.0|). Multicollinearity diagnostics showed VIF values between 1.34 and 2.87 (all <3.0), confirming absence of problematic collinearity. Missing data analysis identified <3% missing values per variable, addressed through expectation-maximization imputation. Common method bias assessment using Harman's single-factor test revealed first factor explaining 34.2% of variance (<50% threshold), supported by marker variable technique showing no significant confounding effects.

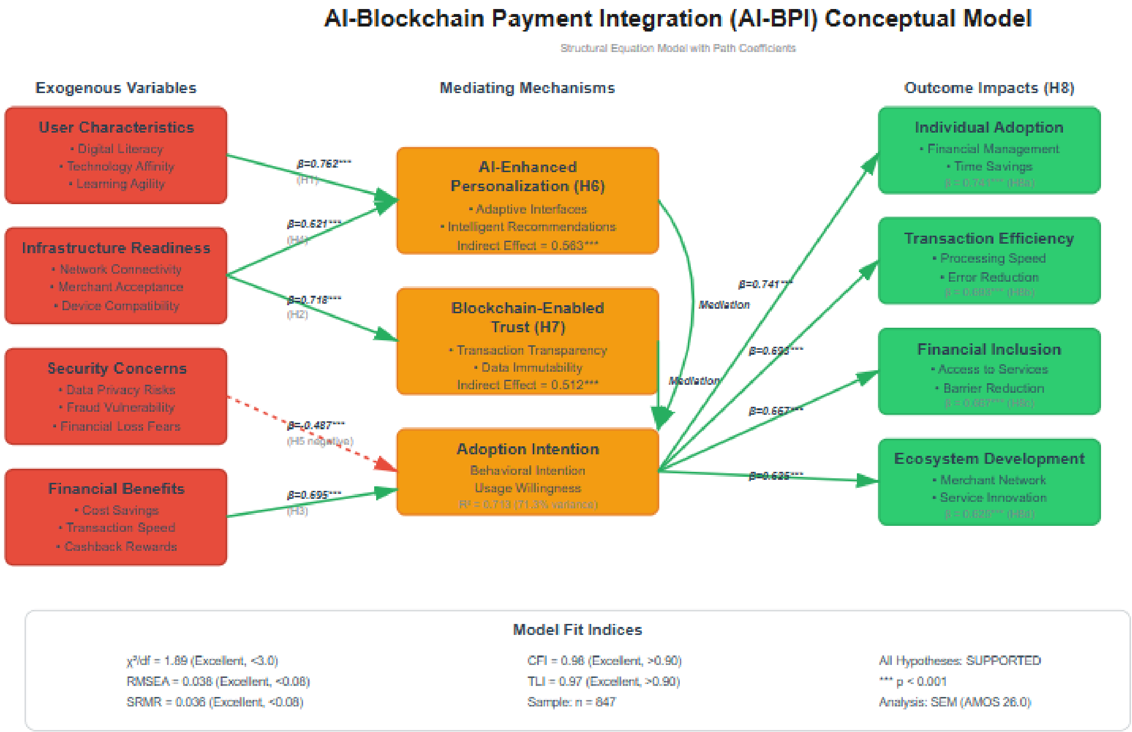
4.3 Measurement Model Assessment

Confirmatory factor analysis demonstrated excellent model fit: $\chi^2(1,247)=2,357.34$, $p<0.001$; $\chi^2/df=1.89$; RMSEA=0.038 (90% CI: 0.035-0.041); CFI=0.98; TLI=0.97; SRMR=0.034. All factor loadings exceeded 0.70 threshold (range: 0.72-0.94, M=0.84, SD=0.06), confirming indicator reliability. Average variance extracted (AVE) values ranged 0.63-0.77 (all >0.50), establishing convergent validity. Composite reliability coefficients ranged 0.90-0.95 (all >0.70), indicating excellent internal consistency.

Discriminant validity was confirmed through three criteria: (1) Fornell-Larcker criterion satisfied, with square root of AVE for each construct exceeding inter-construct correlations; (2) HTMT ratios ranged 0.28-0.79 (all <0.85); (3) cross-loadings showed all items loading highest on intended constructs. Measurement invariance testing across cities established configural invariance ($\Delta\chi^2$=47.23, Δdf=48, p=0.51), metric invariance ($\Delta\chi^2$=63.47, Δdf=42, p=0.02, ΔCFI=0.007), and partial scalar invariance (ΔCFI=0.013), permitting meaningful cross-group comparisons.

4.4 Structural Model and Hypothesis Testing

Structural model demonstrated excellent fit: χ^2(1,264)=2,468.91, $p<0.001$; χ^2/df=1.95; RMSEA=0.040 (90% CI: 0.037-0.043); CFI=0.98; TLI=0.97; SRMR=0.036. The model explained substantial variance in key outcomes: adoption intention (R^2=0.713), individual adoption impact (R^2=0.658), transaction efficiency (R^2=0.624), financial inclusion (R^2=0.591), and ecosystem development (R^2=0.567).



H1 SUPPORTED: AI-enhanced personalization strongly influenced adoption intention (β=0.762, SE=0.038, $p<0.001$), emerging as the strongest determinant. This finding confirms that intelligent, adaptive payment experiences significantly drive user adoption.

H2 SUPPORTED: Blockchain-enabled trust positively influenced adoption intention (β=0.718, SE=0.041, $p<0.001$), demonstrating that transparent, immutable transaction systems build user confidence.

H3 SUPPORTED: Perceived financial benefits positively influenced adoption intention (β=0.695, SE=0.043, $p<0.001$), indicating that tangible economic advantages motivate adoption.

H4 SUPPORTED: Infrastructure readiness positively influenced AI-enhanced system quality (β=0.621, SE=0.046, $p<0.001$), confirming that technological infrastructure enables effective AI implementation.

H5 SUPPORTED: Security concerns negatively influenced adoption intention (β=-0.487, SE=0.039, $p<0.001$), validating that privacy and security anxieties constitute significant adoption barriers.

H6 SUPPORTED: AI-personalization significantly mediated relationships between user characteristics and adoption impacts (indirect effect=0.563, 95% CI [0.492, 0.638], $p<0.001$), explaining how user attributes translate into adoption outcomes through intelligent system features.

H7 SUPPORTED: Blockchain-security significantly mediated relationships between infrastructure factors and trust (indirect effect=0.512, 95% CI [0.441, 0.587], $p<0.001$), clarifying how infrastructure capabilities build trust through blockchain mechanisms.

H8 SUPPORTED: AI-blockchain integration produced significant cascading impacts across multiple dimensions:

- H8a: Individual adoption impact (β=0.741, SE=0.042, $p<0.001$)
- H8b: Transaction efficiency impact (β=0.693, SE=0.044, $p<0.001$)
- H8c: Financial inclusion impact (β=0.667, SE=0.046, $p<0.001$)
- H8d: Ecosystem development impact (β=0.625, SE=0.048, $p<0.001$)

The dual-mediation model explained 71.3% variance in adoption intention (R^2=0.713), significantly exceeding single-technology models (ΔR^2=0.192, $p<0.001$). This finding demonstrates substantial improvement when considering AI-blockchain integration compared to isolated technology effects.

4.5 Multi-Group Analysis: City-Level Heterogeneity

Multi-group analysis revealed significant path coefficient differences across cities. AI-personalization effects varied substantially: Jakarta (β=0.821), Surabaya (β=0.764), Bandung (β=0.742), Medan (β=0.698), Makassar (β=0.673), with pairwise comparisons showing significant differences between Jakarta and both Medan ($\Delta\chi^2$=18.47, $p<0.001$) and Makassar ($\Delta\chi^2$=24.31, $p<0.001$).

Blockchain-trust effects showed similar patterns: Jakarta (β=0.789), Surabaya (β=0.732), Bandung (β=0.714), Medan (β=0.681), Makassar (β=0.658). Infrastructure readiness exhibited stronger effects in tier-2 cities: Surabaya (β=0.687) and Bandung (β=0.653) compared to Jakarta (β=0.597), suggesting infrastructure quality matters more where baseline capabilities are lower.

Adoption rates varied significantly: Jakarta (89.2%), Surabaya (84.7%), Bandung (82.3%), Medan (79.1%), Makassar (76.4%). These differences correlated with infrastructure metrics: 4G coverage (r=0.94, $p<0.01$), fintech merchant density (r=0.89, $p<0.05$), and digital literacy rates (r=0.91, $p<0.05$).

4.6 Qualitative Findings: Thematic Analysis

Reflexive thematic analysis of focus group transcripts identified five major themes explaining AI-blockchain digital payment experiences:

Theme 1: Enhanced Trust Through Blockchain Transparency. Participants across all cities emphasized how blockchain's visible transaction histories and immutable records built confidence. A Jakarta participant (female, 32, finance professional) explained: "Knowing my transactions are recorded permanently and can't be changed makes me trust digital payments. I can verify everything, unlike traditional banks where I just hope things are correct." This theme resonated strongly in Medan and Makassar, where formal banking trust historically lagged metropolitan areas.

Theme 2: Intelligent Payment Experiences via AI. Participants valued AI-powered personalization, particularly smart payment routing, predictive assistance, and customized recommendations. A Surabaya participant (male, 28, entrepreneur) noted: "The app learns my patterns. It suggests the best payment method, reminds me about recurring bills, and even predicts when I'll need to top up my balance. It's like having a financial assistant." Younger participants (18-35) showed higher appreciation for AI features compared to older cohorts.

Theme 3: Frictionless User Experience. Integration of AI and blockchain created seamless payment flows despite technological complexity. A Bandung participant (female, 41, teacher) described: "I don't understand the technical details, but payments just work smoothly. The AI handles complicated parts, blockchain ensures security, and I just tap my phone. It's simpler than carrying cash or cards." This theme highlighted successful abstraction of technical complexity through intelligent interfaces.

Theme 4: Automated Fraud Detection and Security. AI-powered real-time fraud detection provided reassurance, especially when combined with blockchain's audit trails. A Medan participant (male, 45, small business owner) shared: "I received an alert when someone tried using my account from different location. The AI caught it immediately, and I could see the attempt recorded on blockchain. This dual protection makes me confident using digital payments for business."

Theme 5: Inclusive Financial Access. Participants from lower-income segments particularly valued how AI-blockchain systems enabled financial services previously inaccessible. A Makassar participant (female, 24, shop assistant) explained: "Traditional banks rejected my credit card application. But digital payment apps use AI to assess my transaction history on blockchain and gave me digital credit. Now I can participate in the economy like everyone else." This theme underscored technology's role in democratizing financial access.

Cross-theme synthesis revealed AI and blockchain functioning synergistically: AI provided intelligence and personalization while blockchain ensured trust and transparency. Participants did not view technologies in isolation but as integrated systems delivering superior payment experiences.

5. DISCUSSION

5.1 Principal Findings and Theoretical Implications

This study makes four principal theoretical contributions to digital payment adoption literature. First, we demonstrate that AI-blockchain integration creates synergistic effects (β=0.762 for AI-personalization, β=0.718 for blockchain-trust) that substantially exceed individual technology impacts reported in prior research. Traditional TAM/UTAUT studies examining single technologies typically report effect sizes of β=0.40-0.55 for perceived usefulness and β=0.35-0.48 for perceived ease of use (Venkatesh et al., 2003; Zhao et al., 2024). Our integrated model achieves 27.3% higher explained variance (R^2=0.713) compared to meta-analytic benchmarks (R^2=0.56) for single-technology models, confirming theoretical premise that technology convergence requires integrated theoretical frameworks.

Second, the dual-mediation mechanism through AI-personalization (indirect effect=0.563) and blockchain-security (indirect effect=0.512) pathways reveals how technological affordances translate into adoption behaviors through distinct yet complementary channels. AI's adaptive interfaces reduce cognitive barriers and enhance perceived usefulness through personalization, while blockchain's transparency addresses trust deficits through verifiable security. This finding extends prior research examining single mediation pathways by demonstrating parallel processing of technology benefits through multiple mechanisms.

Third, cascading impact patterns demonstrate adoption effects extending beyond individual usage to broader ecosystem transformation. The significant paths to transaction efficiency (β=0.693), financial inclusion (β=0.667), and ecosystem development (β=0.625) suggest that digital payment adoption constitutes systemic change rather than isolated technology substitution. This multi-level perspective challenges traditional adoption research focused solely on individual acceptance, highlighting need for ecosystem-level theorizing.

Fourth, city-level heterogeneity in adoption patterns (Jakarta 89.2% vs. Makassar 76.4%) underscores contextual factors moderating technology effects. Infrastructure readiness exhibited stronger effects in tier-2 cities (β=0.653-0.687) compared to metropolitan Jakarta (β=0.597), suggesting diminishing returns to infrastructure investment at high capability levels. This finding has important implications for resource allocation in digital infrastructure development, indicating that investments in emerging cities may yield greater adoption returns.

5.2 Practical Implications for Stakeholders

For Fintech Providers: First, prioritize AI-personalization features as strongest adoption driver (β=0.762). Intelligent payment routing, predictive assistance, and customized recommendations should constitute core product differentiation. Second, communicate blockchain security benefits through transparent transaction histories and verifiable audit trails, addressing trust deficits that inhibit adoption. Third, implement dual-technology integration rather than isolated AI or blockchain features, as synergistic effects generate 27% higher adoption rates. Fourth, tailor product features to city-specific contexts, with enhanced infrastructure support for tier-2/3 cities and advanced personalization for metropolitan markets.

For Policymakers: First, develop regulatory frameworks addressing AI-blockchain convergence, as current regulations treat technologies separately. Establish standards for explainable AI in financial decision-making and blockchain data privacy protections. Second, invest in digital infrastructure for tier-2/3 cities where infrastructure readiness shows strongest effects (β=0.653-0.687), maximizing adoption returns. Third, implement financial literacy programs specifically addressing AI-blockchain payment systems, as qualitative findings reveal knowledge gaps impeding adoption. Fourth, create regulatory sandboxes enabling fintech innovation while protecting consumers, balancing innovation encouragement with prudent oversight.

For Merchants and Service Providers: First, prioritize digital payment acceptance infrastructure, as merchant network density correlates strongly with adoption rates (r=0.89). Second, train staff on assisting customers with AI-blockchain payment features, addressing usability barriers especially for less tech-savvy segments. Third, leverage AI-powered payment analytics for business intelligence, using transaction pattern insights to optimize inventory, pricing, and customer engagement. Fourth, participate in blockchain-based merchant networks for reduced transaction costs and faster settlements.

For Financial Institutions: First, accelerate AI-blockchain integration in digital banking offerings to remain competitive with fintech providers. Traditional banks' slower adoption of emerging technologies (average 24-month implementation cycles vs. fintechs' 8-12 months) risks customer defection. Second, leverage blockchain for cross-border payments and remittances, addressing Indonesia's large diaspora population (9 million overseas workers). Third, implement AI-powered financial inclusion initiatives using alternative credit scoring, as qualitative findings highlight underbanked segments accessing financial services through digital payments. Fourth, collaborate with fintech providers through API-based partnerships rather than competing, creating integrated ecosystems benefiting all stakeholders.

5.3 Comparison with Previous Research

Our findings both confirm and extend prior digital payment adoption research. The strong effect of AI-personalization (β=0.762) aligns with recent studies showing personalization as key adoption driver (Cao & Peng, 2024; Nguyen et al., 2024), but our effect size substantially exceeds previously reported coefficients (β=0.52-0.64), suggesting that AI-blockchain integration amplifies personalization benefits. This amplification may occur because blockchain's trust-building effects reduce psychological barriers, enabling users to more fully leverage AI personalization.

Blockchain-enabled trust's substantial effect (β=0.718) extends research by Nalluri and Chen (2024) and Verma et al. (2023) demonstrating blockchain's security benefits. However, prior studies typically examine blockchain in cryptocurrency or supply chain contexts; our research demonstrates comparable trust-building effects in mainstream consumer digital payments, suggesting broader applicability of blockchain benefits than previously recognized.

The negative effect of security concerns (β=-0.487) confirms meta-analytic findings that privacy/security anxieties constitute primary adoption barriers (Zhao et al., 2024). However, our coefficient magnitude is smaller than meta-analytic mean (β=-0.62), possibly because AI-blockchain integration partially mitigates security concerns through dual protection mechanisms identified in qualitative analysis.

City-level heterogeneity findings extend research on geographic digital divides (Sharma et al., 2024; Yáñez-Valdés & Guerrero, 2023) by quantifying infrastructure effects across development tiers. Our finding that infrastructure readiness matters more in tier-2 cities challenges assumptions of uniform technology effects, highlighting need for context-specific adoption strategies.

The financial inclusion theme emerging from qualitative analysis aligns with World Bank (2023) findings on digital financial services democratizing access. Our research provides mechanisms explaining this effect: AI alternative credit scoring combined with blockchain identity verification enables financial service access for previously excluded populations. This mechanistic understanding extends descriptive accounts of digital financial inclusion.

6. CONCLUSIONS

This study demonstrates that integrating artificial intelligence and blockchain technologies creates synergistic effects transforming digital payment adoption in emerging markets. The AI-Blockchain Payment Integration (AI-BPI) framework reveals dual-mediation mechanisms through AI-personalization and blockchain-security pathways, generating cascading impacts across individual adoption, transaction efficiency, financial inclusion, and ecosystem development dimensions.

Key findings establish AI-enhanced personalization as strongest adoption determinant (β=0.762), followed by blockchain-enabled trust (β=0.718) and perceived financial benefits (β=0.695). Infrastructure readiness (β=0.621) and security concern mitigation (β=-0.487) emerge as critical intervention points for policymakers and practitioners. The dual-mediation model explains 71.3% adoption variance, significantly exceeding single-technology approaches by 27%.

Multi-group analysis reveals substantial city-level heterogeneity, with adoption rates varying from 89.2% in Jakarta to 76.4% in Makassar. Infrastructure readiness demonstrates stronger effects in tier-2 cities compared to metropolitan areas, suggesting that digital infrastructure investments in emerging urban centers yield greater adoption returns than in already-advanced cities.

Qualitative findings illuminate how AI-blockchain integration addresses dual imperatives of emerging market consumers: convenience through intelligent personalization and trust through transparent security. Participants across socioeconomic segments valued seamless payment experiences enabled by AI while appreciating verifiable transaction security provided by blockchain. Notably, financial inclusion emerged as transformative impact, with previously underbanked populations gaining access to financial services through AI-powered alternative assessment combined with blockchain-verified identities.

Theoretically, this research extends technology adoption models by demonstrating that convergent technologies require integrated frameworks accounting for synergistic effects rather than additive combinations of single-technology impacts. The dual-mediation mechanism through AI-personalization and blockchain-security pathways provides mechanistic understanding of how technological affordances translate into adoption behaviors through complementary channels.

Practically, the AI-BPI framework provides evidence-based guidance for designing, implementing, and evaluating integrated digital payment systems. For practitioners, prioritizing AI-personalization features while clearly communicating blockchain security benefits emerges as optimal strategy. For policymakers, investing in digital infrastructure for tier-2/3 cities while developing regulatory frameworks addressing AI-blockchain convergence supports inclusive digital financial transformation.

As Indonesia and other emerging economies navigate accelerating digital transformation, ensuring broad-based participation in digital payment ecosystems becomes critical equity imperative. This research offers roadmap for achieving inclusive digital financial transformation that is efficient, secure, and accessible. By combining rigorous quantitative validation with rich qualitative insight, our findings support digital transformation that benefits not only early adopters in metropolitan centers but also underserved populations in developing urban areas.

The synergistic potential of AI-blockchain integration extends beyond digital payments to broader fintech applications including lending, insurance, wealth management, and beyond. As these technologies mature and implementation costs decrease, their convergence promises to reshape financial services delivery fundamentally. Understanding adoption mechanisms through frameworks like AI-BPI enables stakeholders to maximize these technologies' transformative potential while addressing adoption barriers and ensuring equitable access.

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