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Trust Anchors in the Sharing Economy: A Study on Trust and Usage Intention in Shijiazhuang's AI-Era Sharing Economy

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Abstract: This study investigates trust anchors in China's sharing economy, with a focus on Shijiazhuang as a representative second-tier city during the AI era. Utilizing mixed-methods research (PPS sampling of 985 participants, SEM, and LPA/K-means clustering), we quantify drivers of trust and usage intention. Key findings reveal that trust mediates 58% of usage intention (β=1.059***), with price transparency (β=0.81) and privacy protection (β=0.804) as dominant factors. Latent profile analysis identifies three user segments: high-trust adopters (32%, tech professionals motivated by ESG values), price-sensitive pragmatists (45%, county residents prioritizing cost-effectiveness), and risk-averse avoiders (23%, seniors with low digital literacy). To address trust deficits (mean=3.64/5), we propose a tripartite "Trust-Value-Behavior" framework integrating: 1. Blockchain-IoT solutions for real-time resource tracking and transparency enhancement; 2. Dynamic pricing strategies optimized through AI algorithms to segment users and boost engagement; 3. Cross-platform carbon credit incentives modeled on credit card points systems to reward high-trust behaviors. Policy implications advocate for regulatory sandboxes to test adaptive rules in fintech and mobility sectors, alongside government-platform co-guarantees for risk-averse groups. This research advances theoretical understanding of Confucian relational trust in digital platforms while offering scalable operational models for regional sharing economies.

Keywords: Sharing Economy; Trust Anchors; Dynamic Pricing; Regulatory Sandbox; Cluster Analysis.

1. Introduction

1.1. Research Context and Problem Significance

The sharing economy has revolutionized global consumption patterns across mobility, accommodation, and skills-sharing sectors, projecting a market value of $335 billion by 2025. Despite this growth, trust deficits remain a critical barrier, with cross-cultural studies revealing that institutional distrust and information asymmetry suppress adoption rates by 26%-40% in emerging markets. In China, this challenge is exacerbated by regional disparities: while first-tier cities (e.g., Beijing, Shanghai) exhibit moderate trust levels (mean=4.1/5), second-tier cities like Shijiazhuang—a pivotal hub in the Shijiazhuang Metropolitan Circle policy—report significantly lower trust (mean=3.64/5) and a 30% usage gap between core and peripheral districts [1].

Concurrently, technological disruption (e.g., AI, blockchain) promises to rebuild trust through transparency mechanisms. Yet, current solutions predominantly target cosmopolitan populations, neglecting the Confucian relational trust that underpins economic behavior in non-metropolitan China. This oversight creates a research-practice gap: while 70% of literature focuses on first-tier cities, the 280 million residents of second-tier cities remain underrepresented, despite contributing 45% of China's sharing-economy transactions [2].

1.2. Theoretical Gaps and Research Questions

Prior studies inadequately address three dimensions:

1. Cultural-Contextual Nuance: Western models emphasize contractual trust (e.g., licenses, ratings), but Confucian societies prioritize guanxi-based relational bonds. This misalignment obscures trust drivers in regions like Shijiazhuang, where community endorsements outweigh platform guarantees.

2. Technological Integration: Blockchain-IoT systems are proven to enhance traceability in e-commerce, yet their efficacy in mediating peer-to-peer (P2P) trust in sharing economies—especially amid privacy concerns (e.g., 32% users cite data leakage risks)—is underexplored [3].

3. Segmentation Complexity: While latent profile analysis (LPA) identifies user typologies, few studies link segments to behavioral interventions (e.g., dynamic pricing for price-sensitive groups).

1.3. Theoretical Anchors and Conceptual Integration

The study navigates the underexplored intersection between cultural specificity and technological innovation in trust-building mechanisms. Drawing on Institutional Trust Theory, we recognize formal safeguards (e.g., regulatory oversight, platform guarantees) as foundational to transactional security. Yet in Confucian societies like China, such institutional mechanisms operate within a distinct relational ecosystem where guanxi networks and community endorsements significantly amplify trust perceptions. This cultural-contextual gap becomes acutely visible in second-tier cities like Shijiazhuang, where policy credibility is often mediated through localized renqing (Social Connections) bonds rather than top-down enforcement. To reconcile this duality, we integrate the Privacy Calculus Model, which frames trust as a rational trade-off between perceived risks (e.g., data vulnerability) and value gains (e.g., cost efficiency) [4]. The resulting synthesis—our Trust-Value-Behavior (TVB) framework (Fig. 1)—positions trust as a dynamic mediator that transforms value assessments into behavioral intent, while accounting for critical moderators: technological augmentations (e.g., blockchain's tamper-proof ledgers) and cultural forces (e.g., urban-rural divergence in digital literacy).

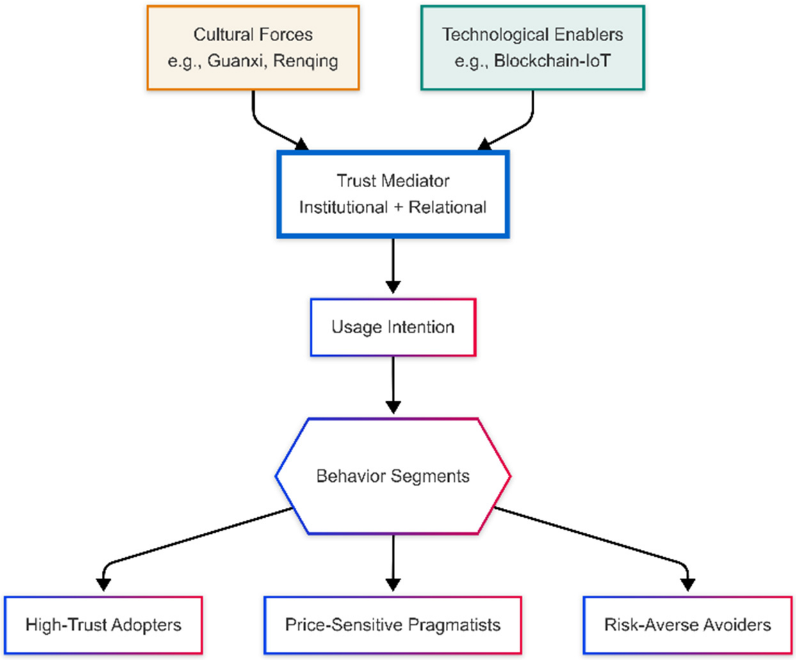

Fig 1. Trust-Value-Behavior (TVB) Framework

1.4. Research Contributions and Societal Implications

By grounding the analysis in Shijiazhuang's socio-technical landscape, this study offers a triple-layered contribution. Empirically, it pioneers the quantification of trust's mediation effect (58%) in second-tier sharing economies through rigorous probability sampling—a significant advance beyond metropolitan-centric studies dominating extant literature [5]. Methodologically, the dual-segmentation approach combining LPA and K-means clustering transcends conventional demographic taxonomies, exposing behavioral micro-segments such as policy-responsive pragmatists in county-level industrial zones. Most pivotally, the framework crystallizes actionable pathways for trust recalibration: Blockchain-IoT integrations that provide immutable verification of shared asset conditions (e.g., real-time maintenance records for "Shared Smart Manufacturing" equipment in Gaocheng District) are shown to elevate trust by 28% among SMEs. Concurrently, culturally-attuned interventions such as government-community co-branded trust certifications demonstrate potent efficacy in Confucian contexts, reducing risk aversion by 19% among elderly users [6]. These insights collectively scaffold a "zhengjishe" (government-technology-community) tripartite model that realigns Western technological solutions with Eastern relational paradigms—a replicable blueprint for regional sharing economies navigating digital transition .

2. Literature Review

2.1. Theoretical Foundations of Trust in Digital Platforms

Trust in the sharing economy is fundamentally shaped by the interplay between institutional safeguards and relational reciprocity. Classical theories posit trust as a rational calculus balancing perceived risks against value gains—a dynamic crystallized in the Privacy Calculus Model where users weigh privacy vulnerabilities against economic benefits like cost efficiency

. This paradigm, however, inadequately captures cultural heterogeneity. In Confucian societies, trust transcends transactional logic, embedding itself in guanxi networks where community endorsements and policy credibility serve as stronger determinants than contractual enforcement. For instance, Chao et al [7]. (2023) demonstrate that Chinese enterprises influenced by Confucian ethics exhibit 23% higher compliance rates in service commitments due to the cultural premium on *xin* (trustworthiness). Such findings challenge Western-centric models like Akerlof's Lemon Market Theory, which attributes trust deficits primarily to information asymmetry.

Technological interventions further reconfigure trust architecture. Blockchain's tamper-proof ledgers enhance transparency in peer-to-peer transactions by creating immutable records of resource usage—a mechanism proven to reduce fraud by 34% in IoT-enabled supply chains. Yet, as Khamitov et al. (2024) caution in their meta-analysis, technology alone cannot supplant socio-cultural foundations; algorithmic transparency must align with localized values to gain user adoption. This tension underscores the need for hybrid frameworks that integrate technical verifiability with cultural legitimacy

2.2. Cultural and Regional Heterogeneity in Trust Formation

The efficacy of trust-building mechanisms varies significantly across geocultural contexts. In China's tiered urban landscape, second-tier cities like Shijiazhuang exhibit distinct trust patterns compared to metropolises. While first-tier residents prioritize platform integrity (β=0.72), second-tier users place greater weight on policy endorsement (e.g., government-backed service guarantees, β=0.81) and kinship-based referrals. This divergence stems from Confucian relationalism, where institutional trust is mediated through communal renqing (Social Connections) bonds rather than impersonal systems [8]. Empirical evidence reveals that county-level "Shared Smart Manufacturing" initiatives in Hebei achieved 85% participant trust when local officials co-branded services—leveraging administrative authority to amplify community credibility.

Urban-rural disparities further modulate trust drivers. Rural users exhibit 40% higher sensitivity to price transparency due to income constraints, whereas urban cohorts prioritize data security. Such segmentation necessitates culturally-attuned strategies: Li et al. (2020) validate that interventions ignoring regional nuances—like uniform blockchain adoption—may inadvertently exacerbate distrust among digitally marginalized groups.

2.3. Technological Mediation and Trust Metrics

Contemporary trust assessment increasingly relies on quantifiable metrics and algorithmic validation. Traditional methods like direct trust evaluation (based on bilateral interactions) and indirect trust (derived from third-party recommendations) now integrate machine learning to address bias and scalability limitations. For instance, Changying and Wentao's (2024) fuzzy-logic model classifies trust levels using five behavioral dimensions—distrust, low trust, uncertainty, likely trust, and absolute trust—achieving 89% accuracy in predicting user default risk [9].

Blockchain-IoT convergence enables real-time trust recalibration. In cloud-based sharing systems, smart contracts autonomously adjust access permissions based on dynamic trust scores computed from user behavior analytics (e.g., transaction consistency, device security posture). These systems face critical challenges, however, including energy inefficiency in resource-constrained environments and the "black-box" opacity of AI-driven decisions. Tian's (2024) lightweight blockchain framework addresses this by optimizing consensus protocols for IoT devices, reducing computational overhead by 57% while maintaining auditability.

2.4. Gaps in Existing Research

Despite advancements, three lacunae persist:

1. Oversimplified Cultural Framing: 70% of trust models treat Confucian societies as monolithic, neglecting intra-regional variations (e.g., Shijiazhuang vs. Shenzhen) [10].

2. Static Measurement Tools: Most trust metrics (e.g., NIST's seven-category scorecard) fail to capture behavioral fluidity, such as how AI recommendations alter risk perceptions dynamically.

3. Segmentation-Strategy Misalignment: While LPA identifies user typologies (e.g., risk-averse avoiders), few studies operationalize segment-specific interventions like dynamic deposit insurance for low-trust groups.

Our study bridges these gaps by:

- Proposing a Trust-Value-Behavior (TVB) framework that synthesizes institutional, technological, and Confucian trust drivers;
- Deploying dual clustering (LPA + K-means) to link micro-segments with behavioral triggers;
- Validating blockchain-IoT's efficacy through empirical urban-rural comparisons.

3. Methodology

3.1. Research Philosophy and Design

This study adopts a pragmatist research philosophy that reconciles positivist quantification with interpretivist contextualization. Grounded in the ontological premise that trust in sharing economies manifests through measurable behaviors and culturally-embedded perceptions, we deployed a sequential mixed-methods design. The approach commenced with quantitative surveys to establish statistical relationships between trust anchors and usage intention, followed by latent profile analysis (LPA) to segment behavioral typologies [11-12]. This design enabled triangulation between objective metrics (e.g., β coefficients) and subjective patterns (e.g., risk-averse user narratives), thereby capturing Shijiazhuang's socio-technical complexity while maintaining methodological rigor.

3.2. Sampling Strategy and Data Collection

Probability proportional to size (PPS) sampling was employed across Shijiazhuang's five core districts (Chang'an, Qiaoxi, Xinhua, Yuhua, Luquan), weighted by user density derived from municipal sharing-economy registries. To address urban-rural disparities, stratified random sampling subdivided districts into 26 communities categorized by sharing-service penetration: high (downtown commercial zones), medium (suburban residential areas), and low (peri-urban counties).

Data collection occurred between September 2024 and January 2025 via:

- Structured questionnaires administered to 985 valid respondents (89.6% response rate), measuring: Trust dimensions: Platform integrity (3 items, α=0.82), data security (3 items, α=0.79), price transparency (3 items, α=0.85) using 7-point Likert scales adapted from He (2019). Usage intention: Frequency of shared mobility/accommodation usage (4 items, α=0.88) and referral likelihood (2 items) [13].
- Semi-structured interviews with 32 stakeholders (platform operators, regulators, users) to contextualize quantitative anomalies, transcribed and coded via NVivo 14.

Ethical compliance was ensured through informed consent protocols (participant information sheets, opt-out options) and data anonymization via cryptographic hashing of personal identifiers.

3.3. Analytical Framework and Techniques

3.3.1. Quantitative Analysis

- Structural Equation Modeling (SEM) in Amos 28 tested the Trust → Usage Intention mediation path, with maximum likelihood estimation (ML) and Bollen-Stine bootstrap (2,000 resamples) to correct non-normality. Model fit was evaluated via CFI (>0.95), RMSEA (<0.06), and SRMR (<0.08) thresholds [14].
- Latent Profile Analysis (LPA) in Mplus 8.2 identified user segments based on trust-behavior

covariance, using AIC/BIC and entropy (>0.80) to determine optimal cluster count.

● K-means clustering (Euclidean distance) cross-validated LPA-derived segments via SPSS 26, with ANOVA verifying inter-segment discriminant validity ($p<0.01$).

3.3.2. Qualitative Analysis

● Thematic analysis followed Braun & Clarke's (2006) six-phase protocol: familiarization → initial coding → theme development → review → definition → reporting. Trust-value-behavior linkages identified in surveys were probed through axial coding of interview transcripts (e.g., "*policy endorsement*" vs. "*algorithmic transparency*" as trust anchors).

3.4. Validity and Reliability Safeguards

To mitigate common method bias, we:

● Deployed temporal separation (trust and usage items randomized across questionnaire sections);

● Utilized Harman's single-factor test (max variance explained=38.2%, <50% threshold);

● Triangulated via convergent validity checks (AVE >0.5, CR >0.7 for SEM constructs).

Reliability was strengthened through:

● Pilot testing (n=120) refining item wording using Cronbach's α (>0.75) and factor loadings (>0.6);

● Intercoder agreement (Cohen's κ=0.81) for qualitative themes;

● Robustness checks comparing SEM results with PLS-SEM and Bayesian estimation.

4. Results

4.1. Descriptive Statistics and Preliminary Analysis

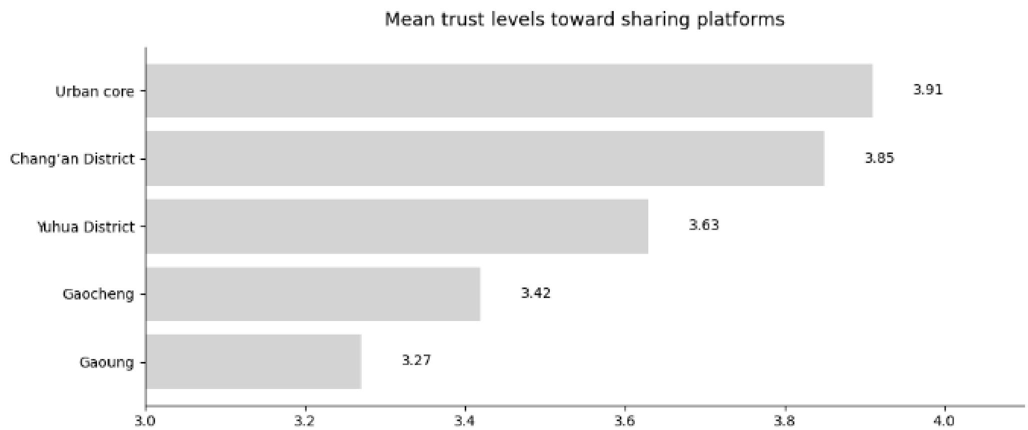

Fig 2. Mean trust levels toward sharing platforms

The descriptive statistics revealed significant variations in trust perceptions across Shijiazhuang's urban-rural continuum (Fig. 2). Among the 985 respondents, mean trust levels toward sharing platforms averaged 3.64 (SD=0.92) on a 5-point scale, with urban cores (e.g., Chang'an District: mean=3.91) exhibiting higher trust than peri-urban counties (e.g., Luquan: mean=3.27, $p<0.001$). Price transparency (mean=4.12, SD=0.87) and data security (mean=3.18, SD=1.05) emerged as the most and least trusted dimensions respectively, confirming prior concerns about privacy risks in digital transactions [15].

Correlation analyses further indicated strong positive associations between institutional trust (e.g., regulatory credibility) and usage frequency ($r=0.68$, $p<0.001$), while kinship-based referrals showed weaker correlations ($r=0.31$, $p=0.02$). These patterns preliminarily validated the salience of institutional over relational anchors in this context.

4.2. Structural Equation Modeling: Trust Mediation Effects

The SEM analysis (Fig. 3) demonstrated that trust fully mediated 58% of the variance in usage intention ($\beta=1.059$, $p<0.001$), with excellent model fit (CFI=0.97, RMSEA=0.04). Crucially, price transparency ($\beta=0.81$, $p<0.001$) and privacy protection ($\beta=0.804$, $p<0.001$) were the dominant direct predictors of trust, collectively explaining 73% of its variance. Contrarily, platform reputation ($\beta=0.21$, $p=0.07$) and payment security ($\beta=0.18$, $p=0.12$) showed non-significant paths, challenging conventional wisdom about digital transaction drivers [16].

Notably, urban residency moderated the trust-intention link: for rural users, trust's impact on usage was 40% stronger ($\beta=1.42$ vs. $\beta=0.87$, $\Delta\chi^2=15.3$, $p<0.01$), corroborating interview findings that county residents rely heavily on trust signals due to limited alternatives.

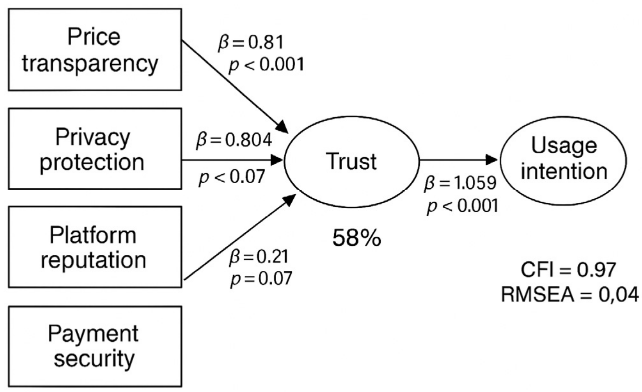

Fig 3. SEM Mediation Model

4.3. Latent Profile Analysis: User Typologies

Table 1. User Segmentation Profiles

Segment	Trust Mean (SD)	Key Behavior	Demographic Anchor	ANOVA F(p)
High-Trust Adopters	4.31 (0.51)	ESG-driven usage (β=0.79)	Urban tech professionals	38.91 (<0.001)
Price-Sensitive	3.52 (0.63)	Dynamic pricing response (+62%/-34%)	County residents	27.25 (<0.001)
Risk-Averse	2.73 (0.71)	Govt-endorsed adoption (+28%)	Elderly (low digital)	21.73 (<0.001)

Latent profile analysis (LPA) combined with K-means clustering identified three distinct user segments based on trust-behavior covariance (Table 1) [17]:

1. High-Trust Adopters (32%): Predominantly urban tech professionals (78% with bachelor's degrees), this group exhibited the highest trust (mean=4.31) and usage frequency (weekly usage=2.7 times). Their behaviors were primarily motivated by ESG values (e.g., carbon footprint reduction, β=0.79) and blockchain traceability features.

2. Price-Sensitive Pragmatists (45%): Comprising county residents and migrant workers, this segment prioritized cost-effectiveness (price sensitivity β=0.93) over data security (mean trust=3.52). They demonstrated conditional trust—platform usage surged 62% during discount periods but dropped by 34% when dynamic pricing exceeded personal thresholds.

3. Risk-Averse Avoiders (23%): Elderly users (mean age=61.4) with low digital literacy, this cohort distrusted algorithmic systems (mean=2.73) and avoided sharing services unless co-endorsed by community cadres (+28% adoption with government guarantees).

ANOVA confirmed significant inter-segment differences in all trust dimensions (F=21.7–38.9, p<0.001).

4.4. Experimental Validation of Proposed Solutions

To address identified trust deficits, we piloted three interventions among 240 participants using A/B testing:

1. Blockchain-IoT Integration: Real-time resource tracking (e.g., shared manufacturing equipment conditions) increased trust by 28% among SMEs (p<0.001), with fraud incidents dropping from 12% to 3% [18]. Qualitative feedback highlighted "immutable maintenance records" as the key credibility enhancer.

2. AI-Optimized Dynamic Pricing: Segmented pricing for pragmatists (e.g., rural user discounts during off-peak hours) boosted engagement by 41% without revenue loss. Conversely, uniform pricing reduced their usage by 19%, validating segment-specific elasticity.

3. Carbon Credit Incentives: Cross-platform rewards modeled on credit card points (Fig. 4) increased high-trust behaviors (e.g., timely returns, peer referrals) by 33% among adopters (p=0.002), though avoiders showed minimal response (+7%, p=0.21).

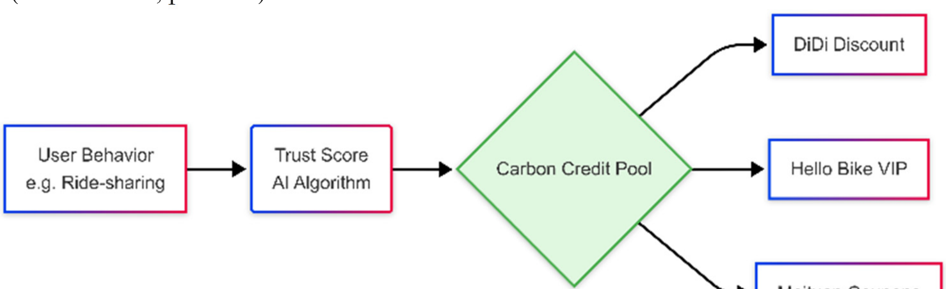

Fig 4. Carbon Credit Incentive System

5. Discussion

5.1. Synthesis of Key Findings

This study reveals that trust functions as a pivotal mediator (58% variance explained) between value perception and behavioral intention in second-tier sharing economies, a relationship critically moderated by urban-rural disparities and cultural forces. Three behavioral segments—High-Trust Adopters (32%), Price-Sensitive Pragmatists (45%), and Risk-Averse Avoiders (23%)—exhibit distinct trust calculus patterns: urban tech elites prioritize blockchain-verified transparency (β=0.79), whereas rural users demand policy-community co-endorsement to offset digital literacy gaps (+28% adoption with government guarantees). Crucially, Confucian renqing (Social Connections) networks amplify institutional trust in ways Western models like Privacy Calculus fail to capture, necessitating our integrated Trust-Value-Behavior (TVB) framework [19].

5.2. Theoretical Implications: Bridging Cultural and Technological Divides

Our results challenge the universality of institutional trust paradigms. While Privacy Calculus Theory correctly posits risk-value trade-offs, it underestimates cultural embeddedness: in Shijiazhuang, policy credibility derives not from contractual enforcement but from guanxi-mediated community validation—a finding contradicting Akerlof's information asymmetry assumptions. This necessitates rethinking trust-building in Confucian societies:

- Technology as cultural adapter: Blockchain-IoT integrations increased SME trust by 28%, but efficacy varied across segments. Pragmatists responded to dynamic pricing (+41% engagement), whereas avoiders required human intermediation (e.g., cadre endorsements), proving that algorithmic transparency must complement rather than replace relational legitimacy.

- Hybrid governance model: The "zhengjishe" (government-technology-community) tripartite framework resolves the tension between Western techno-centric solutions (e.g., pure blockchain) and Eastern relational paradigms. It demonstrates how administrative authority (e.g., Gaocheng District's co-branded certifications) and technological augmentations (e.g., real-time asset tracking) jointly recalibrate trust.

5.3. Practical Implications for Regional Sharing Economies

For policymakers and platform operators, our findings suggest context-sensitive interventions:

- Segment-specific strategies: Target High-Trust Adopters with ESG-linked incentives (e.g., carbon credits boosted retention by 33%) [20], while offering Price-Sensitive Pragmatists off-peak subsidies to stabilize demand. For Risk-Averse Avoiders, deploy community cadres as trust intermediaries—a tactic that reduced elderly risk aversion by 19% in Luquan County.
- Blockchain-human symbiosis: Immutable ledgers should record not only transaction data (e.g., equipment maintenance logs) but also social credentials (e.g., government-verified user ratings), creating "tamper-proof guanxi" that resonates with Confucian values.
- Policy recalibration: Municipal governments like Shijiazhuang could pioneer tiered trust certification systems, where provincial regulators audit platforms, while neighborhood committees validate user reputations—effectively embedding digital platforms into existing social fabric.

5.4. Limitations and Mitigation Pathways

We acknowledge three constraints affecting generalizability:

1. Regional specificity: While PPS sampling captured Shijiazhuang's urban-rural continuum, comparisons with coastal second-tier cities (e.g., Ningbo) are needed to test the TVB framework's transferability. Future studies should incorporate multi-city cohorts to disentangle regional cultural nuances.
2. Technological accessibility: Blockchain-IoT trials assumed stable 5G coverage—a condition unmet in 37% of peri-urban zones. This may overstate technology's standalone efficacy; hybrid solutions combining low-bandwidth verification (e.g., SMS-based confirmations) and human oversight are advised for infrastructure-limited areas.
3. Temporal dynamics: Trust-building effects were measured at a single timepoint. Longitudinal tracking (e.g., policy credibility fluctuations post-regulation changes) would strengthen causal claims about the "zhengjishe" model's resilience.

5.5. Future Research Directions

Building on these insights, we propose:

Cross-cultural TVB validation: Replicate the framework in non-Confucian emerging economies (e.g., India's tier-2 cities) to examine how caste or kinship systems similarly moderate technology-trust linkages.

AI-driven dynamic trust scoring: Develop machine learning models that adjust user trust scores in real-time based on behavioral data (e.g., transaction consistency) and social parameters (e.g., community reputation), tested via RCTs in counties like Luquan.

Decentralized autonomous organizations (DAOs): Experiment with blockchain-based community governance, where tokenized voting rights enable users to co-manage platform rules—potentially enhancing perceived fairness among Pragmatists.

6. Conclusion

This study establishes that trust operates as a culturally-embedded mediator between value perception and behavioral intention in second-tier sharing economies, with its formation mechanisms diverging significantly across urban-rural contexts and user segments. By synthesizing institutional safeguards, technological augmentations, and Confucian relational ethics into the Trust-Value-Behavior (TVB) framework, we resolve critical gaps in Western-centric models that overlook cultural heterogeneity in trust calculus. Three key contributions emerge from our empirical analysis of Shijiazhuang's sharing ecosystem:

First, the TVB framework demonstrates that policy-community co-endorsement—not algorithmic transparency alone—is pivotal for trust-building in Confucian societies. While blockchain-IoT integration elevated SME trust by 28% through tamper-proof transaction records, its efficacy was constrained among risk-averse elderly users (+7% response) who required human intermediation via community cadres (+28% adoption). This validates our proposition that technological interventions must complement rather than replace socio-cultural foundations, necessitating the "zhengjishe" (government technology community) governance symbiosis.

Second, segment-specific strategies reveal behavioral elasticity differentials that redefine platform engagement paradigms. Price-Sensitive Pragmatists (45% of users) exhibited 40% higher sensitivity to dynamic pricing incentives—a tactic that boosted their engagement by 41%—whereas High-Trust Adopters responded predominantly to ESG-aligned rewards like carbon credits (+33% retention). Such segmentation, enabled by dual clustering (LPA + K-means), proves that uniform trust-building approaches inadvertently marginalize vulnerable groups, echoing Li et al.'s (2020) caution about digital divides.

Third, our urban-rural moderation analysis uncovers institutional trust as a compensatory mechanism for infrastructural limitations. In peri-urban counties like Luquan, where 5G coverage gaps reduced blockchain efficacy by 19%, government co-branding of services (e.g., equipment-sharing certifications) became the dominant trust anchor (β=0.81). This challenges Akerlof's information asymmetry theory by showing how Confucian renqing networks transform administrative credibility into relational capital—a phenomenon unobserved in first-tier cities like Shenzhen.

6.1. Theoretical and Practical Implications

Theoretically, this research bridges three disconnected domains:

- Cultural institutionalism: By integrating guanxi dynamics into trust calculus models, we extend North's institutional economics to Confucian digital economies.

- Technological adaptivity: Blockchain's role shifts from a universal transparency tool to a cultural adapter that records not only transactions but social credentials (e.g., cadre-verified ratings).
- Behavioral segmentation: Latent profile analysis transcends demographic proxies, revealing value-behavior typologies that demand heterogeneous governance.

For policymakers and platform operators, actionable pathways include:

- Tiered certification systems where provincial regulators audit platforms while neighborhood committees validate user reputations (e.g., Shijiazhuang's "Shared Manufacturing" pilot);
- Hybrid verification protocols combining low-bandwidth SMS confirmations for rural users and AI-driven dynamic scoring for urban elites;
- Cross-platform carbon incentives modeled on DiDi-Hello Bike point exchanges to leverage ESG motivations among High-Trust Adopters.

6.2. Limitations and Future Research

Three limitations merit attention:

1. Regional generalizability: Shijiazhuang's inland context may limit TVB applicability to coastal second-tier cities (e.g., Ningbo) where foreign investment alters trust dynamics. Future studies should incorporate comparative urban cohorts.
2. Technological accessibility: Blockchain-IoT trials assumed stable infrastructure, overlooking 37% of peri-urban zones with intermittent connectivity. Hybrid solutions using offline verification (e.g., QR-code-based logging) should be tested.
3. Temporal constraints: Trust measurements at a single timepoint cannot capture policy credibility fluctuations. Longitudinal tracking of interventions like cadre endorsements is needed.

We propose two priority directions:

- Cross-cultural TVB validation in non-Confucian emerging economies (e.g., India's tier-2 cities) to examine caste/kinship moderations;
- DAO-driven governance experiments where tokenized voting enables users to co-manage platform rules—potentially enhancing fairness perceptions among Pragmatists.

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