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PROCEEDING BOOK

Innovating Finance in the Age of AI: Balancing Automation and Human Insight

4th October 2025

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Chiang Mai University
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We extend our heartfelt appreciation to Mr. Tobias Mostert Wickens, Expert in Macroeconomic Statistics at the International Monetary Fund (IMF), for delivering an insightful keynote address titled “The International Monetary Fund (IMF) and the Role of Macroeconomic Statistics in Economic Policymaking and Analyses.” His lecture provided valuable perspectives on the intersection between global economic data, policymaking, and financial innovation—perfectly aligned with this year’s conference theme, “Innovating Finance in the Age of AI: Balancing Automation and Human Insight.”

Special recognition is extended to all student authors for their dedication and scholarly contributions to this proceedings volume. Your research represents the continuing advancement of graduate-level inquiry in the areas of digital innovation, financial technology, and artificial intelligence.

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Finally, we wish to express our deep gratitude to the leadership of the International College of Digital Innovation, Chiang Mai University, for their steadfast encouragement and continued commitment to promoting academic excellence, innovation, and research collaboration.

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08:45 - 09:00	Opening Speech by Asst. Prof. Dr. Rujira Ouncharoen Dean, International College of Digital Innovation
09:00 - 10:00	Keynote Talk: "The International Monetary Fund (IMF) and the Role of Macroeconomic Statistics in Economic Policymaking and Analyses" by Mr. Tobias Mostert Wickens Expert in Macroeconomic Statistics, International Monetary Fund (IMF)
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CONTRIBUTED TALK SCHEDULE

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A Trust Analysis of Curve and Uniswap in Stablecoin Trading Based on the Invariant of AMMs

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ABSTRACT

Decentralized exchanges (DEXs) like Curve and Uniswap are central to Decentralized Finance (DeFi), especially for stablecoin trading that requires both efficiency and dependable trust mechanisms. We compare Curve and Uniswap across four trust dimensions: security, liquidity, cost-effectiveness (fees), and reliability, using the May 2022 UST depegging event as a case study. We combine quantitative data analysis of Total Value Locked (TVL) and trading volume from DeFiLlama (2025) with qualitative insights from Chainalysis reports (2022, 2023). Our findings reveal distinct trust profiles. Curve provides lower fees and deep liquidity, making it more cost-efficient for stablecoin swaps, but it also shows notable vulnerability to security exploits. Uniswap, while generally more expensive, has a stronger security record and broader liquidity base, supporting its reliability even under regulatory scrutiny. The study offers practical guidance for three audiences: users choosing between platforms, developers seeking to improve protocol resilience, and regulators assessing systemic stability in DeFi. Methods include Pearson correlations of TVL and UST price and a 7-day rolling volatility measure derived from log-returns.

KEYWORDS: Decentralized Finance, Automated Market Maker (AMM), Trust Analysis, Stablecoin, Curve Finance, Uniswap, Security, Liquidity

1 INTRODUCTION

Decentralized Finance (DeFi) has changed how global markets operate by using blockchain technology and smart contracts to deliver services without banks or other intermediaries (Nakamoto, 2008; Ethereum, 2015). One key mechanism driving this change is the Automated Market Maker (AMM), a decentralized exchange (DEX) model that replaces order books with algorithm-driven liquidity pools. Two protocols, Uniswap and Curve Finance, have become the most influential examples of this design, supporting heavy trading activity and serving as central platforms for stablecoin swaps.

Figure 1 (Web-1) compares the Total Value Locked (TVL) in Curve DEX (blue) and Uniswap V3 (red), 2021– 2025. Curve peaked above $25B in early 2022 but lost significant liquidity during the May 2022 UST collapse and the July 2023 exploit, stabilizing near $2B by 2025. Uniswap V3 maintained lower TVL overall ($3–7B) but avoided extreme crashes, illustrating greater resilience under stress. Source: DeFiLlama (2025).

Uniswap, launched in 2018 and upgraded to V3 in 2021, is a general-purpose AMM built to handle diverse token pairs. The V3 model introduced concentrated liquidity, allowing capital to be allocated more efficiently within chosen price ranges. This feature helped Uniswap maintain a large share of DeFi activity in stablecoin trading, with a Total Value Locked (TVL) of about $39 billion as of early 2025 (Uniswap Blog, 2023; DeFiLlama, 2025).

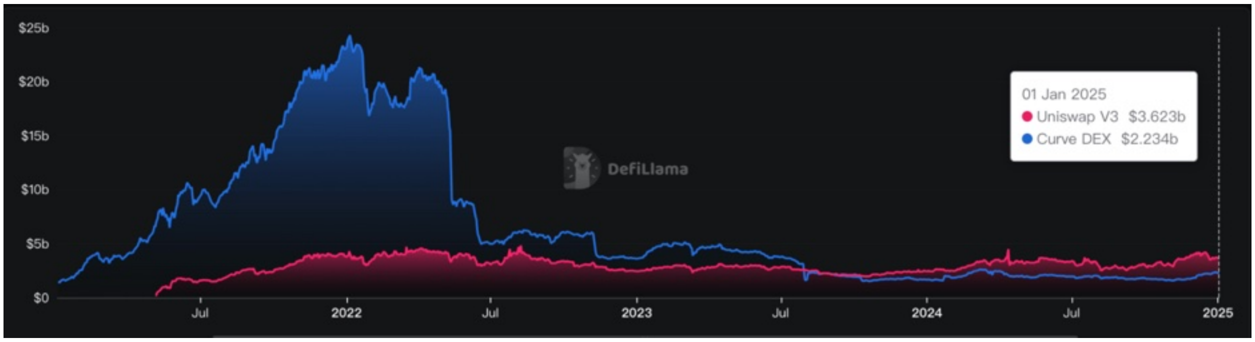

Figure 1: TVL comparison of Curve vs Uniswap (Web-1)

Curve Finance, by contrast, launched in 2020 with a narrower focus: trading pegged assets such as USDT, USDC, and DAI. Its StableSwap algorithm reduces slippage for assets of similar value, bringing in large amounts of liquidity and pushing its 3pool (USDT/USDC/DAI) to a peak TVL of $25 billion in 2022 (Curve Resources, 2023; Origin Protocol, 2023).

Users and institutions rely on trust to adopt and keep using these platforms. That trust depends on four factors: security (resistance to exploits), liquidity (depth of TVL and trading volume), costs (transaction fees), and reliability (uptime and crisis response) (Chen & Bellavitis, 2020). Weakness in any of these areas can quickly erode confidence. Two stress events illustrate this vulnerability: the May 2022 collapse of TerraUSD (UST), which erased tens of billions of dollars in value and destabilized liquidity pools across DeFi (Chainalysis, 2022), and the July 2023 exploit of Curve Finance, where attackers stole about $70 million by exploiting a vulnerability in smart contracts, shaking user confidence despite partial recoveries (Chainalysis, 2023).

Few academic studies directly compare the trustworthiness of Curve and Uniswap in stablecoin trading. Existing analyses often focus only on headline metrics and overlook qualitative context (Coin360, 2023). This study fills that gap by comparing Curve and Uniswap across the key dimensions of trust, using both empirical data and case evidence. The study aims to support user decision-making and highlight areas for protocol improvement. More broadly, it helps explain how trust is built and tested in DeFi.

2 LITERATURE REVIEW

2.1 DeFi, AMMs, and the Importance of Stablecoins

The foundation of DeFi was established by Nakamoto (2008), who introduced a peer-to-peer electronic cash system operating without central intermediaries. Ethereum's launch of smart contracts in 2015 enabled programmable financial applications, making Automated Market Makers (AMMs) possible (Ethereum, 2015). The Total Value Locked (TVL) in DeFi surpassed $100 billion by early 2025, showing the scale of this ecosystem (DeFiLlama, 2025). Stablecoins—cryptocurrencies pegged to assets such as the US dollar—play a central role in DeFi. They are designed to reduce volatility and function as a medium of exchange, accounting for more than 60% of trading volume on major platforms (Investopedia, 2024; DeFiLlama, 2025). Their stability underpins the operation of AMM pools.

2.2 Protocol Mechanisms: Uniswap vs. Curve

Uniswap, launched in 2018, has evolved through several versions, with V3 introducing concentrated liquidity. This feature allows Liquidity Providers (LPs) to allocate capital within selected price ranges, improving efficiency for stablecoin pairs (Uniswap Blog, 2023). Pricing remains based on the constant product formula (x * y = k). Uniswap v3 also offers multiple fee tiers (0.05%, 0.3%, and 1%), with this study focusing on the standard 0.3% tier.

Curve Finance, launched in 2020, was built specifically for trading pegged assets such as USDT, USDC, and DAI. Its StableSwap invariant blends constant product and constant sum formulas, reducing slippage for similar-value tokens (Coin Bureau, 2023; Curve Resources, 2023). This design supports very low fees (0.04%) and has consistently attracted deep liquidity in its stablecoin pools (Curve Resources, 2023; Gemini, 2023). TechDreams (2021) described Curve as an especially efficient mechanism for swapping pegged assets. Governance adds another layer of trust: Curve's DAO, structured around the CRV token, determines incentives and parameter updates, and Gemini (2023) notes that this governance model shapes both liquidity and reliability.

2.3 Constructing Trust in DeFi Protocols

Trust in DeFi depends on several factors. Chen and Bellavitis (2020) highlighted liquidity depth and low transaction costs as drivers of adoption. Security is equally important; the July 2023 Curve exploit, caused by a reentrancy vulnerability, led to losses of about $70 million and showed how technical flaws can quickly undermine user confidence (Chainalysis, 2023). In contrast, Uniswap's record of avoiding major breaches has reinforced its reputation for reliability (RR² Capital, 2023). Governance transparency, often delivered through Decentralized Autonomous Organizations (DAOs), also contributes to trust by involving token holders in decision-making (Moralis Academy, 2023; Gate Ventures, 2023). The UST collapse of May 2022 further tested AMM resilience, revealing vulnerabilities in both protocol design and crisis communication (Chainalysis, 2022).

2.4 Research Gap

The literature documents Uniswap's contributions to liquidity innovation and Curve's efficiency in stablecoin trading. However, comparative work often remains shallow, focusing on individual metrics such as TVL while neglecting a broader evaluation of security, costs, liquidity under stress, and governance (Coin360, 2023). This study develops an integrated trust analysis of Curve and Uniswap, combining metrics often examined separately in prior work.

3 METHODOLOGY

This study combines quantitative analysis of protocol data with qualitative case studies of major stress events.

3.1 Data Collection

Quantitative data on Total Value Locked (TVL) and daily trading volume were retrieved from the DeFiLlama API (DeFiLlama, 2025). The analysis focused on:

Curve: the 3pool (USDT, USDC, DAI), representing its main stablecoin liquidity pool.

Uniswap: stablecoin pairs (USDC/USDT) and stablecoin-ETH pairs (USDC/ETH, USDT/ETH), capturing broader liquidity dynamics.

The dataset covers January 2020 to February 2025, a period that includes the UST depeg (May 2022) and the Curve exploit (July 2023). Fee structures were taken from protocol documentation (Curve: 0.04%; Uniswap v3: standard 0.3% tier). Qualitative data were taken from Chainalysis reports on the UST depeg and the Curve hack (Chainalysis, 2022, 2023).

3.2 Quantitative Data Analysis Using jamovi

All quantitative data were analyzed using jamovi. The specific analytical procedures for each objective are outlined below.

Preprocessing. UST closing prices were aligned with TVL and VOL series by their DATE fields. The VOL columns in the dataset represent daily changes (returns), not volatility. To measure "true volatility," a 7-day rolling standard deviation (σ) of TVL log-returns was calculated.

Correlation model. Pearson's product–moment correlation was used to quantify linear associations among UST closing price, TVL (Curve and Uniswap), and trading volume. The coefficient is:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{(n-1)s_x s_y} \tag{1}$$

where $\overline{x}$, $\overline{y}$ are sample means and s_x, s_y are sample standard deviations. Two-tailed tests were conducted with α=0.05. P-values and 95% confidence intervals were generated in jamovi with pairwise deletion for missing data.

Variables:

UST_PRICE = daily UST close (USD)

TVL_CUR, TVL_UNI = daily total value locked for Curve and Uniswap

VOL_CUR, VOL_UNI = daily trading volume

VOL7_CURVE, VOL7_UNI = true 7-day rolling volatility of TVL (σ of log-returns)

Hypotheses for each protocol and metric pair:

H_0: $r = 0$ (no linear association)

H_1: $r \neq 0$ (linear association present)

Significance was evaluated at α=0.05 (two-sided). Effect sizes are reported as r with 95% confidence intervals where relevant.

Statistical analysis. Pearson correlations were computed among UST price, TVL, and volatility measures. Pairwise deletion was applied to missing observations. A collapse-window filter (May–June 2022) was used to isolate the UST depeg period.

3.2.1 Quantitative Trend Analysis

TVL and trading volume were examined around the UST depeg to evaluate how liquidity shifted during the event.

3.2.2 Correlation Analysis (Exploratory)

The analysis tested how UST price movements correlated with TVL and trading volume to assess how the two protocols responded to external shocks.

3.2.3 Qualitative Case Studies

Two qualitative case studies supplemented the quantitative work: the UST depegging (May 2022) and the Curve exploit (July 2023). These episodes illustrate the impact of smart contract flaws and asset instability on protocol trust, with Curve's case also involving partial white-hat fund recovery.

4 RESULTS AND DISCUSSION

4.1 Liquidity Depth and Resilience

TVL data show Curve held the largest share of stablecoin liquidity, with its 3pool reaching a peak of $25B in 2022. Uniswap, by contrast, maintained a larger overall TVL ($39B as of early 2025), reflecting its broader range of assets and trading pairs.

The UST collapse in May 2022 was a major test of AMM liquidity. Figure 3 shows that both protocols experienced significant strain. Curve's TVL fell by nearly one-third within days, while Uniswap's decline was more moderate. This drop reflects Curve's exposure to UST-linked assets and its greater fragility under stablecoin shocks. This fragility is reinforced by Curve's liquidity composition. As shown in Figure 2, most of Curve's pools were concentrated in just three asset categories—ETH, stETH, and stablecoins. Such concentration supports deep liquidity under normal conditions but leaves the protocol highly vulnerable when any of these assets lose stability, as occurred with the stETH de-pegging in May 2022.

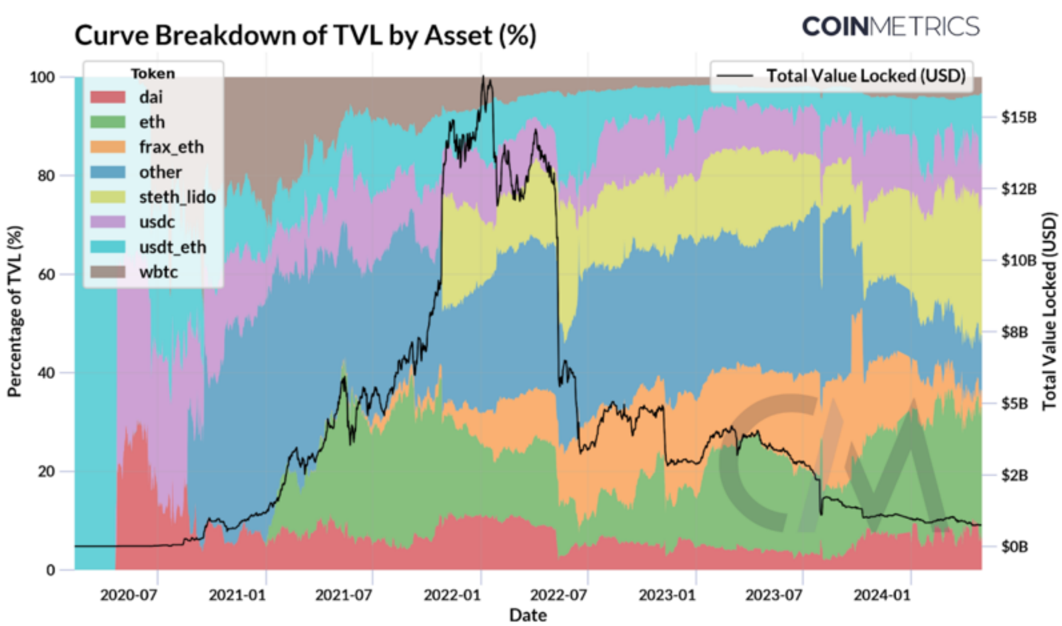

Figure 2: Composition of liquidity on Curve by asset type (ETH, stETH, stablecoins, and others). Source: Coin Metrics DeFi Balance Sheets & Labs.

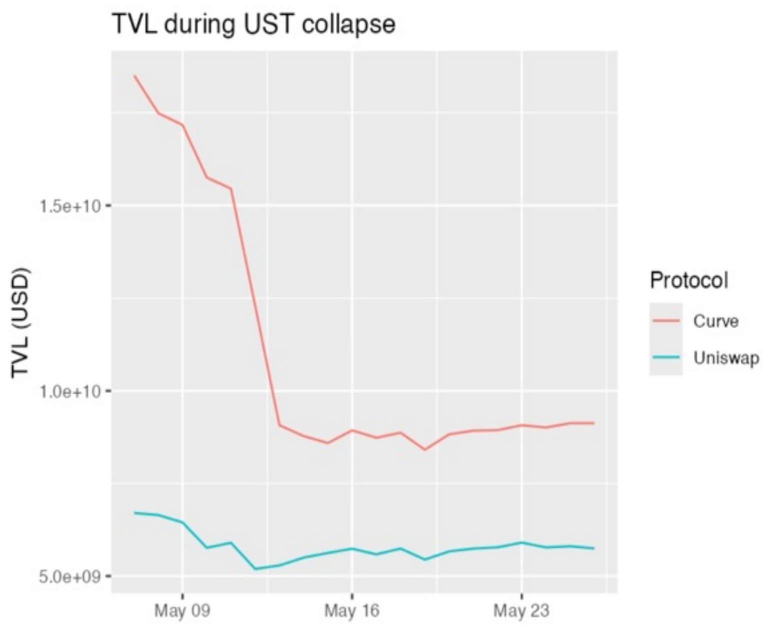

Figure 3: TVL during UST collapse: Curve vs. Uniswap.

4.2 Correlation Between TVL and UST Price

Pearson correlations during the collapse window (May 7–26, 2022) show that Curve's TVL was almost perfectly tied to UST price ($r = .986$, $p < .001$, 95% CI [.965, .995]). Uniswap's TVL was also significantly correlated but at a more moderate level ($r = .700$, $p < .001$, 95% CI [.373, .872]). In contrast, trading volumes displayed weak and non-significant associations with UST price (Curve: $r = -.170$, $p = .474$; Uniswap: $r = -.320$, $p = .168$). The two protocols' TVLs, however, were strongly associated with each other ($r = .745$, $p < .001$, 95% CI [.450, .893]). Taken together, the results indicate that Curve's liquidity was far more sensitive to UST stability, while Uniswap exhibited a looser but still meaningful linkage.

Table 1 Pearson correlations among UST price, TVL, and reported volumes. Values are Pearson's r with two-tailed p-values (pairwise deletion). Author's computation in jamovi (collapse window: May 7–26, 2022).

Correlation Matrix

		TVL_CUR	TVL_UNI	UST_PRICE	VOL_CUR	VOL_UNI
TVL_CUR	Pearson's r	—				
	df	—				
	p-value	—				
	95% CI Upper	—				
	95% CI Lower	—				
TVL_UNI	Pearson's r	0.745 ***	—			
	df	18	—			
	p-value	< .001	—			
	95% CI Upper	0.893	—			
	95% CI Lower	0.450	—			
UST_PRICE	Pearson's r	0.986 ***	0.700 ***	—		
	df	18	18	—		
	p-value	< .001	< .001	—		
	95% CI Upper	0.995	0.872	—		
	95% CI Lower	0.965	0.373	—		
VOL_CUR	Pearson's r	−0.132	0.395	−0.170	—	
	df	18	18	18	—	
	p-value	0.580	0.085	0.474	—	
	95% CI Upper	0.330	0.713	0.295	—	
	95% CI Lower	−0.543	−0.057	−0.570	—	
VOL_UNI	Pearson's r	−0.346	0.126	−0.320	0.477 *	—
	df	18	18	18	18	—
	p-value	0.136	0.598	0.168	0.033	—
	95% CI Upper	0.114	0.538	0.142	0.759	—
	95% CI Lower	−0.684	−0.336	−0.668	0.044	—

Note. * p < .05, ** p < .01, *** p < .001

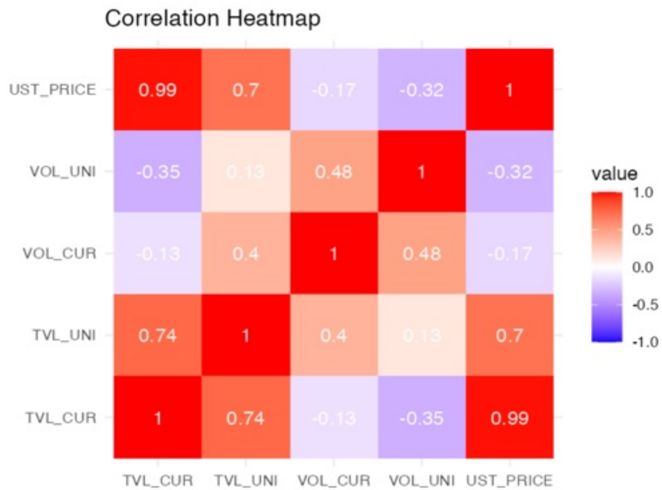

Figure 4: Correlation heatmap of UST price, TVL, and volume. Cells show Pearson's r; asterisks mark significance ($p < .05$, $p < .01$, $p < .001$). Author's computation in jamovi (collapse window: May 7–26, 2022; dataset described in §3.1).

4.3 Reported VOL (Dataset Returns)

Figure 5 shows the "reported VOL" columns provided in the dataset. These values do not represent statistical volatility (σ), but daily percentage changes in TVL. Because of this, the series can take both positive and negative values. Sharp spikes, including plunges below –20, reflect large negative daily changes during the UST collapse, not negative volatility. This measure shows short-term directional stress but misses overall variability.

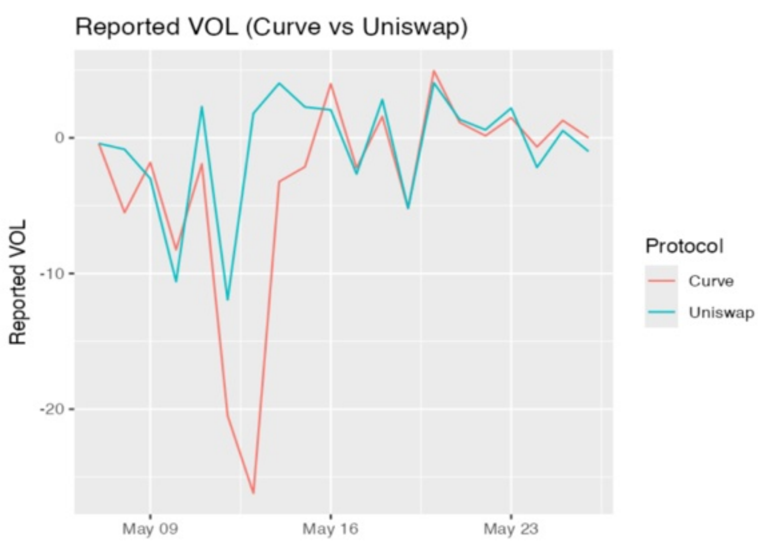

Figure 5: Reported VOL.

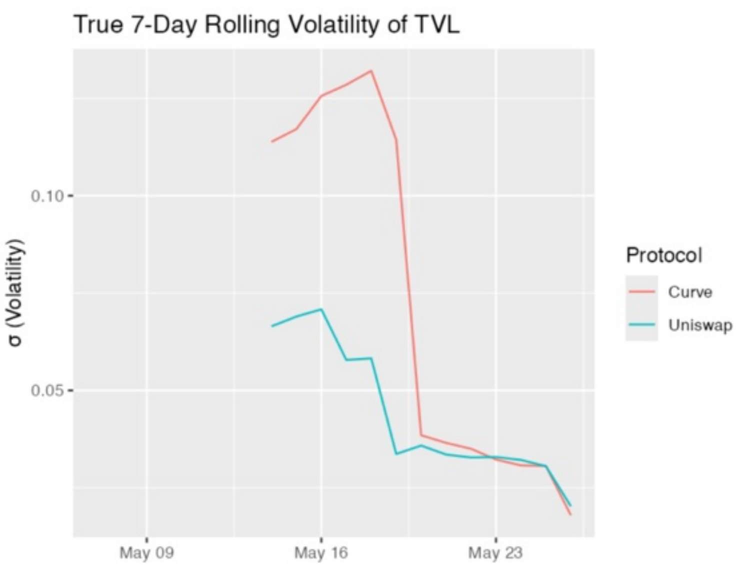

Figure 6: 7-Day Rolling Volatility.

4.4 True Volatility (Rolling 7-Day σ)

Figure 6 presents the true volatility measure, calculated as the 7-day rolling standard deviation of TVL log-returns (see §3.2). Unlike the reported VOL series, this measure is strictly non-negative and reflects variability in liquidity rather than directional changes. Volatility for Curve rose sharply after the May 7 depeg, while Uniswap's increase was more limited, which aligns with its more diversified pool structure.

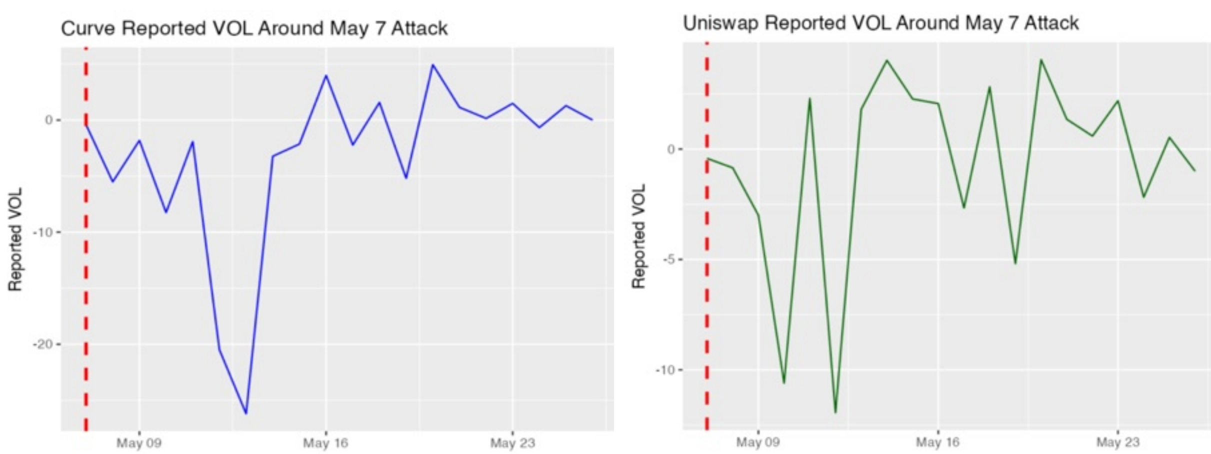

Figure 7: Curve and Uniswap Reported VOL around May 7. (dataset described in §3.1)

4.5 Governance and Emergency Measures

Governance and emergency safeguards also play a central role in shaping trust. Curve's sharp outflows suggest inadequate protective measures (e.g., circuit breakers or liquidity backstops) and weak communication during the UST collapse. Uniswap, by contrast, benefited from broader pool diversification and did not experience the same degree of stress. Three factors emerge as especially important for long-term trust:

Technical stability: the ability to withstand shocks without catastrophic liquidity loss.

Governance transparency: how clearly risks and emergency measures are communicated.

Risk resilience: whether protocols have circuit breakers, diversified pools, or insurance reserves.

Taken together, the findings show that protocols need safeguards such as circuit-breakers, liquidity backstops, and standardized communication protocols, as discussed further in the Conclusion.

4.6 Synthesis of Trust Profiles

The evidence points to two distinct trust profiles:

Curve: efficient and liquid for stablecoin swaps, but highly vulnerable when pegged assets fail and limited in crisis response.

Uniswap: broader liquidity and stronger resilience to shocks, with a better historical security record, though less cost-efficient for stablecoin trading.

Overall, the findings show that protocols need safeguards such as circuit-breakers, liquidity backstops, and standardized communication protocols, as discussed further in the Conclusion.

Table 2 Summary comparison of Curve vs. Uniswap across trust dimensions. (Sources: protocol documentation; DeFiLlama; Chainalysis; author's computations in jamovi.)

Dimension	Curve (stablecoin-specialized)	Uniswap (general-purpose, v3)
Fees	~0.04% typical stable pools	Fee tiers 0.05%, 0.3%, 1.0% (this study uses 0.3%)
Liquidity scope	Deep stablecoin pools (e.g., 3pool)	Broad asset coverage, large aggregate TVL
Security history	July 2023 exploit (~$70M) with partial recovery	No comparable major protocol-level exploit reported
Event sensitivity	Higher sensitivity to stablecoin stress (UST collapse)	Smaller TVL drawdown in UST window
Volatility (σ)	Larger spike in rolling 7-day σ post–May 7, 2022	Smaller σ increase, more diversified pools
Governance	CRV-centric DAO; incentives tied to stable pools	UNI governance; broad tokenholder base

4.7 Limitations

This study has several limitations that should be acknowledged. First, the analysis relies on secondary data sources (DeFiLlama for liquidity metrics and Chainalysis for incident reporting), and no independent on-chain validation was performed. Second, the focus on Curve and Uniswap provides insight into two major protocols but limits the generalizability of findings to the broader AMM ecosystem. Third, the correlation analysis identifies linear associations but cannot establish causality, and other factors such as macro-market conditions were not explicitly modeled. Finally, the collapse window analyzed (May–June 2022) is relatively short, which constrains statistical power and may affect the stability of some estimates.

Future research could address these issues by incorporating additional protocols, validating data directly on-chain, and modeling broader market drivers alongside protocol-specific dynamics.

5 CONCLUSION

This study provides a comparative trust analysis of Curve and Uniswap during the UST collapse and later stress scenarios. The data show that Curve, while highly cost-efficient and holding deep stablecoin liquidity, is structurally fragile when underlying assets lose stability. In contrast, Uniswap, though less cost-efficient, experiences more moderate declines and lower volatility, which suggests greater resilience. Based on these findings, three sets of recommendations emerge:

5.1 For Protocol Developers

Protocol developers should implement circuit breakers and liquidity backstops to pause trading or stabilize pools during abnormal volatility. Diversifying liquidity pools beyond a narrow set of pegged assets can reduce systemic risk. In addition, continuous security audits and expanded bug bounty programs are needed to reduce the risk of exploits.

5.2 For Regulators

Regulators should create frameworks requiring real-time disclosure of liquidity risks and governance decisions during crises. Insurance reserves or decentralized insurance pools should be encouraged or mandated to protect users. Regulators must also monitor systemic risks tied to stablecoin-dependent protocols, given how quickly problems can spread through these systems.

5.3 For Users and Institutional Investors

Users and institutional investors should adopt a diversified strategy, balancing cost-efficient but fragile platforms such as Curve with more resilient options like Uniswap. Platforms with stronger governance transparency and proven resilience during instability should be prioritized.

Curve is efficient but fragile, while Uniswap is more reliable though less cost-efficient. To build sustainable trust in DeFi, protocols will need stronger technical safeguards, clearer governance, and institutional-grade risk management. For Curve, future strategies should focus on building risk-management infrastructure without losing its cost advantage. For Uniswap, reducing cost barriers while navigating regulation effectively will be crucial. If adopted, these measures would strengthen trust in DeFi and help it withstand future crises.

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Intelligent Estimation of Building Costs Through Case-Based Reasoning Approach

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ABSTRACT

Accurate building cost estimation remains challenging due to dynamic variables such as material prices, labor, location, and regulatory changes. Traditional models which concern Quantity Surveying, Parametric Estimation, Regression Analysis, and Analogous Estimation often fail to address real-world complexities, resulting in inaccurate forecasts and financial risk. This study proposes a Case-Based Reasoning (CBR) model that leverages historical project data for flexible, context-aware predictions. The four-phase CBR cycle includes: (1) Retrieve similar cases via weighted similarity, (2) Reuse by adapting cost components, (3) Revise using expert or market input, and (4) Retain the new case to enhance learning. Experiments on five benchmark datasets show CBR achieves the lowest MAPE (7.2%-9.7%), outperforming Regression (9.8%-12.4%) and Quantity Surveying (up to 16.1%). CBR also showed better adaptability (4.8-5.0) and learning efficiency (10-14% gains). This paper contributes a knowledge-driven estimation framework and offers a practical, intelligent tool for modern construction management.

KEYWORDS: case-based reasoning, cost estimation, construction management, adaptive systems, machine learning, project forecasting

INTRODUCTION

One main problem in intelligent estimation of building costs is the inability to accurately adapt to dynamic variables and project-specific complexities (Zhang, 2024). Construction costs are influenced by numerous fluctuating factors such as material prices, labor availability, geographic location, economic conditions, and regulatory standards. Traditional estimation methods often struggle to incorporate these variables effectively, especially when data is inconsistent, outdated, or unavailable (Luttikhuis, 2025). This results in cost predictions that lack precision and reliability, leading to budgeting errors, project delays, and financial risks. A more adaptive and context-aware approach is needed to handle the complexity and diversity of modern construction environments.

To address the challenges in building cost estimation, four traditional models have been commonly applied: Quantity Surveying, Parametric Estimation, Regression Analysis, and Analogous Estimation (Yi & Luo, 2024). The Quantity Surveying Model involves a comprehensive breakdown of every component in the building, assigning unit prices to each item based on standardized data. It is detailed and accurate but time-consuming and requires substantial manual effort. The Parametric Estimation Model uses statistical correlations between historical data and project parameters like area, number of floors, or construction type. It is quicker than quantity surveying and useful in early planning stages but may be less accurate for unique projects. The Regression Analysis Model builds mathematical equations using historical data to predict costs based on project features. This model can handle large datasets and identify trends but assumes linear relationships and requires clean, structured data. Finally, the Analogous Estimation Model draws on similar past projects to estimate new costs. It is fast and intuitive but depends heavily on expert judgment and can be biased or imprecise without a strong comparative framework (Naderi et al., 2025). These models provide foundational tools for cost estimation, yet they often fall short in adapting to complex or evolving construction scenarios, paving the way for intelligent systems like Case-Based Reasoning.

Table 1 Traditional Model

Traditional Model	Purpose	Key Features
Quantity Surveying Model (Valinejadshoubi et al., 2024)	To calculate detailed and itemized costs based on actual project elements	High accuracy, detailed measurement, relies on standardized unit costs
Parametric Estimation Model (Paris et al., 2025)	To estimate costs using project parameters and statistical relationships	Fast estimation, based on historical data trends, suitable for conceptual design phase
Regression Analysis Model (Alshibani et al., 2025)	To predict costs through mathematical modeling of historical project data	Identifies patterns, uses statistical methods, requires clean and structured datasets
Analogous Estimation Model (Habib et al., 2025)	To estimate costs by comparing with similar completed projects	Quick and intuitive, uses expert knowledge, sensitive to case relevance and expert judgment

The Case-Based Reasoning (CBR) model solves the main problem of inaccurate and inflexible building cost estimation by leveraging past project experiences to intelligently predict future construction costs (Sohrabi & Noorzai, 2024). Instead of relying on static formulas or subjective expert judgment, CBR retrieves the most relevant historical cases based on project similarities such as building type, size, materials, and location. These cases are then adapted to fit the new project's unique context, adjusting for factors like inflation or regulatory changes. This dynamic retrieval and adaptation process allows the model to generate more accurate and context-aware estimates, even in situations with incomplete or uncertain data (Long & Anh, 2024). Additionally, CBR continuously learns by retaining new cases and outcomes, thereby enhancing its accuracy over time. Its ability to reason from real-world examples and incorporate new information makes it particularly effective for complex and evolving construction environments, offering a scalable and intelligent alternative to traditional estimation methods (Wang et al., 2024).

This research offers three contributions: theoretically, it advances cost estimation by introducing a knowledge-driven CBR framework that learns from historical data; practically, it delivers a model enabling adaptive, accurate estimates across diverse building scenarios; and prospectively, it establishes a foundation for intelligent decision-support that evolves with complexity, reduces human error, and improves resource planning, bridging historical knowledge and contemporary challenges.

RELATED WORKS

Historical Development of Cost Estimation Techniques in Construction

The evolution of construction cost estimation techniques has moved from manual and experience-based practices to structured and algorithm-driven approaches. Early models relied heavily on Quantity Surveying, involving manual measurement and bill of quantities, which, although precise, were slow and labor-intensive. The rise of statistical methods introduced Parametric Estimation and Regression Analysis, allowing for faster calculations based on historical cost patterns and project attributes (Yang et al., 2022). However,these techniques are limited by their assumptions of linearity and inability to adapt to non-standardized data. This historical progression highlights the increasing demand for flexible and intelligent systems that can accommodate both structured and unstructured inputs, setting the foundation for AI-based approaches such as Case-Based Reasoning.

Parametric and Regression Models for Cost Prediction

Parametric and regression models have been widely adopted for early-stage cost prediction due to their ability to identify relationships between cost drivers and total project cost. These models use variables such as building area, floor count, and material types to derive formulas that predict cost outcomes.While efficient, they often lack the contextual nuance needed for complex projects. Studies such as those by Kim et al. (2004) and Hegazy & Ayed (1998) emphasize the limitations of regression models when applied to non-linear or incomplete datasets (Shamim et al., 2025). As construction data becomes more varied and real-time, these traditional models increasingly fail to provide the accuracy and adaptability needed for effective cost estimation.The diversity of parametric models is shown in Figure 1, with common techniques such as regression analysis and function point analysis. While useful for generalizing cost drivers, they often fail to adapt to complex projects.

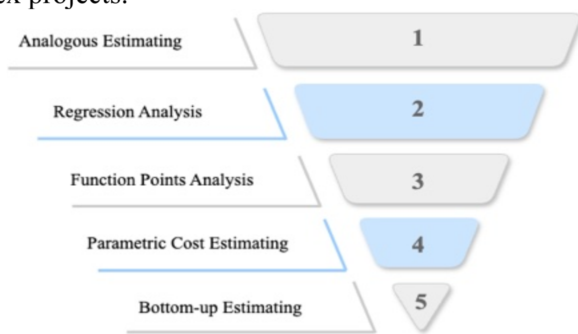

Figure 1:Parametric Estimation Models Types

Machine Learning Applications in Construction Estimation

Recent research has explored the use of machine learning (ML) for improving prediction accuracy in construction cost estimation (Wang et al., 2024). Techniques such as artificial neural networks, decision trees, and support vector machines have shown promise in capturing complex, non-linear patterns in historical data. These models can generalize from training data to predict unseen project scenarios, and some have been integrated into BIM environments. However, ML models often require large, clean datasets and lack interpretability, which can make them difficult to deploy in practical settings.

Case-Based Reasoning and Its Comparative Performance in Construction Cost Estimation

Case-Based Reasoning (CBR) has been effectively applied across various engineering domains, including fault diagnosis, mechanical design, and risk assessment (Chen et al., 2022). In construction, CBR supports bidding decisions, delay assessments, and safety recommendations by leveraging an experiential knowledge base to adapt past solutions to new contexts.

Comparative studies highlight that CBR outperforms traditional estimation models, particularly in complex projects where contextual variables play a significant role. For example, Goh and Chua (2000) found that CBR provided more accurate cost predictions than regression analysis in residential building projects. Furthermore, CBR's ability to continuously learn from new cases reduces estimation error over time, offering enhanced adaptability and scalability in dynamic construction environments (Uysal & Sonmez, 2023). As a result, CBR is increasingly recognized as a practical AI-driven tool that bridges the gap between expert knowledge and data-driven prediction systems.

RESEARCH METHODOLOGY

Conceptual Model for Building Costs

The Case-Based Reasoning (CBR) model (shown in Figure 2) addresses the problem of inaccurate and rigid building cost estimation by implementing a four-phase cycle: Retrieve, Reuse, Revise, and Retain (Yan & Cheng, 2024). When a new project requires a cost estimate, the system first identifies and extracts relevant features such as project type, area, materials, location, labor rates, and timeline. In the Retrieve phase, these input attributes are compared with a historical case base using a similarity function, allowing the system to identify the most analogous past cases. The Reuse phase adapts the retrieved case's cost structure to reflect the new project's specific context, such as adjusting unit costs for inflation, labor availability, or regional pricing. In the Revise phase, the estimated output is validated using either domain knowledge, expert feedback, or real-time constraints. Corrections are incorporated to improve prediction accuracy. Lastly, the Retain phase stores the new project case, its inputs and verified output into the case base to enhance future estimations. This cycle enables continuous learning and improves adaptability across diverse construction scenarios (Sohrabi & Noorzai, 2024).

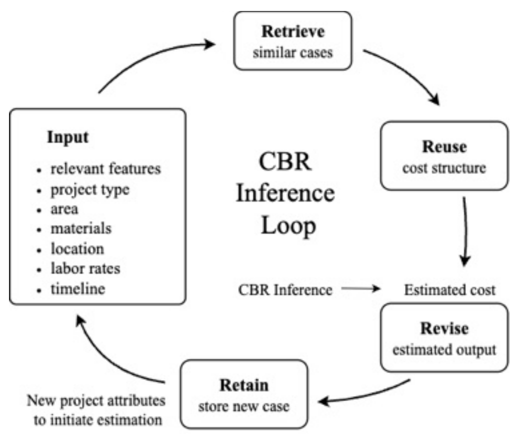

Figure 2: The Proposed CBR Framework

Algorithm Design of CBR for Building Costs

The CBR algorithm offers a structured, adaptive method for estimating building costs through four steps: Retrieve, Reuse, Revise, and Retain. It retrieves similar past cases, reuses relevant data, revises estimates with expert input or market indices, and retains new cases for future use. This process enables context-sensitive predictions and continuous improvement, enhancing accuracy in data-limited or complex settings. By leveraging historical project databases, CBR improves estimation reliability and integrates smoothly with AI tools and industry data pipelines, making it a practical solution for dynamic construction scenarios.

```
def cbr_cost_estimation(newProject, caseBase):
    (i) Retrieve – Identify the most similar case:
        retrievedCase = retrieve_similar_case(newProject, caseBase)
    (ii) Reuse – Adapt the solution to the current project:
        adaptedCost = reuse_case(retrievedCase, newProject)
    (iii) Revise – Incorporate feedback and refine the estimate:
        finalEstimatedCost = revise_cost(adaptedCost, newProject)
    (iv) Retain – Store new case for future use:
        updatedCaseBase = retain_case(newProject, finalEstimatedCost, caseBase)
    return finalEstimatedCost, updatedCaseBase
```

Evaluation

1.Mean Absolute Error (MAE) is one of the simplest and most widely used metrics for evaluating cost estimation models. It calculates the average absolute difference between the actual costs and the predicted costs (Hodson, 2022). This metric treats all errors equally, making it easy to interpret. The formula is given by:

$$\text{MAE} = \frac{1}{n}\sum |\, y_i - \hat{y}_i \,| \qquad (1)$$

where y_i is the actual cost, $\hat{y}_i$ is the predicted cost for the i-th project, and n is the total number of projects. A lower MAE indicates that the model produces predictions that are close to the actual values.

2.Root Mean Squared Error (RMSE) is a more sensitive metric that penalizes larger errors more severely than MAE (Hodson, 2022). It does so by squaring the difference between actual and predicted values before averaging and then taking the square root.The formula is:

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \qquad (2)$$

Lower RMSE values indicate better model performance.

3.Mean Absolute Percentage Error (MAPE) expresses the error as a percentage of the actual value, allowing for intuitive comparisons across different scales and project sizes (Chicco et al., 2021). It is calculated as:

$$MAPE = \frac{100\%}{n}\sum \left|\frac{y_i - \hat{y}_i}{y_i}\right| \qquad (3)$$

Lower MAPE values indicate a more accurate model, making it easier for stakeholders to assess performance.

4.The Coefficient of Determination (R²Score) evaluates how well the model explains the variability of the actual cost values (Reddy & Henze, 2023) . It compares the total squared error of the model against the total variance in the actual data. The equation is:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \qquad (4)$$

where $\hat{y}_i$ is the mean of the actual values. And R^2value close to 1 indicates that a large proportion of the variance in actual costs is captured by the model, whereas a value near 0 suggests poor predictive power. Negative values can also occur, indicating that the model performs worse than simply using the mean of the actual values.

Data source

Table 2 presents five UCI datasets applicable to construction cost estimation using Case-Based Reasoning. Each dataset offers structured attributes related to materials, energy efficiency, or labor economics.

Table 2 Data source

Dataset Name	Purpose	Key Features	Target Variable(s)
Concrete Compressive Strength(θ_1) (Altuncı, 2024)	To predict the strength and quality of concrete mixtures	Cement, Slag, Fly Ash, Water, Superplasticizer, Aggregates, Age	Compressive Strength (MPa)
Energy Efficiency(θ_2) (Li et al., 2025)	To model energy performance in building designs	Surface Area, Wall/Roof Area, Glazing Area, Height, Orientation	Heating and Cooling Load
Residential Building Data Set (θ_3) (Ntakolia et al., 2022)	To evaluate thermal and energy behavior of residential structures	Window Size, Surface Area, Volume, Roof Type, Building Shape	Heating Load, Cooling Load
Combined Cycle Power Plant (θ_4) (Asghar et al., 2023)	To predict energy output from plant environmental and operational data	Temperature, Pressure, Vacuum, Humidity	Energy Output (MW)
Adult (Census Income)(θ_5) (Islam et al., 2023)	To predict income level based on demographic and employment characteristics	Age, Education, Occupation, Work Hours, Marital Status	Income Level (>50K or <=50K)

RESULTS AND DISCUSSION

In Table 3, which reports Mean Absolute Percentage Error (MAPE %), CBR consistently achieves the lowest error rates, ranging from 7.2% to 9.7%, outperforming traditional models like Regression Analysis (9.8%-12.4%) and Quantity Surveying (up to 16.1%). This indicates CBR's superior prediction accuracy in diverse scenarios. Table 4 illustrates the Accuracy Score (%), where CBR again leads, scoring between 90.0% and 94.1%. In comparison, Regression Analysis ranks second with 86.0% to 90.2%, while Quantity Surveying has the lowest accuracy scores, ranging from 82.52% to 87.03%.

Moving to Table 5, which measures Adaptability to Contextual Variables on a 0-5 scale, CBR scores consistently high, between 4.8 and 5.0, showing its strong capability to adjust to varying conditions such as labor costs, location, and regulatory factors. Traditional models, especially Quantity Surveying and Parametric Estimation, display limited adaptability (mostly below 3.0), indicating rigidity in dynamic environments. Finally, Table 6 evaluates Learning Efficiency, reflecting the percentage improvement over time. CBR again dominates with gains between 10% and 14%, benefiting from its case memory and continuous learning capability. In contrast, Quantity Surveying shows no learning capacity, while other models show minimal improvement (2%-6%). Collectively, the data across Tables 3 to 6 confirm that CBR not only delivers higher accuracy and lower error but also offers better adaptability and learning potential, making it the most intelligent and future-ready solution for building cost estimation in complex, real-world construction projects (Uysal & Sonmez, 2023).

Table 3 Comparative Performance (MAPE %) on Multiple Datasets

Dataset	Quantity Surveying Model	Parametric Estimation Model	Regression Analysis Model	Analogous Estimation Model	CBR
θ_1	14.20%	11.80%	10.30%	12.50%	8.10%
θ_2	13.90%	12.40%	11.10%	11.90%	7.60%

Dataset	Quantity Surveying Model	Parametric Estimation Model	Regression Analysis Model	Analogous Estimation Model	CBR
θ_3	15.30%	13.50%	12.20%	14.10%	9.00%
θ_4	12.80%	10.60%	9.80%	11.50%	7.20%
θ_5	16.10%	14.00%	12.40%	15.00%	9.70%

Table 4 Accuracy Score (%) by Model and Dataset

Dataset	Quantity Surveying Model	Parametric Estimation Model	Regression Analysis Model	Analogous Estimation Model	CBR
θ_1	85.61%	88.23%	89.71%	87.52%	92.4%
θ_2	86.12%	87.40%	88.93%	88.10%	93.0%
θ_3	83.24%	85.50%	87.81%	84.22%	90.1%
θ_4	87.03%	89.42%	90.20%	88.32%	94.1%
θ_5	82.52%	84.21%	86.00%	83.51%	90.0%

Table 5 Adaptability to Contextual Variables (0–5 Scale)

Dataset	Quantity Surveying Model	Parametric Estimation Model	Regression Analysis Model	Analogous Estimation Model	CBR
θ_1	2.10	2.52	3.03	3.51	5.0
θ_2	2.50	3.05	3.21	3.72	5.0
θ_3	2.04	2.61	3.10	3.32	4.9
θ_4	2.32	2.90	3.42	3.51	5.0
θ_5	1.90	2.42	2.82	3.10	4.8

Table 6 Learning Efficiency (Improvement Over Time %)

Dataset	Quantity Surveying Model	Parametric Estimation Model	Regression Analysis Model	Analogous Estimation Model	CBR
θ_1	0.01%	3.01%	5.01%	6.04%	12%
θ_2	0.03%	2.05%	4.03%	5.02%	14%
θ_3	0.02%	3.02%	5.05%	5.01%	11%
θ_4	0.04%	4.02%	6.01%	6.04%	13%
θ_5	0.01%	2.03%	4.00%	5.02%	10%

CONCLUSION

This study introduced a Case-Based Reasoning (CBR) approach to address the critical limitations of traditional building cost estimation methods. Conventional models such as Quantity Surveying, Parametric Estimation, Regression Analysis, and Analogous Estimation, while foundational, often lack adaptability to manage dynamic variables like fluctuating material prices, regional labor costs, and regulatory changes. In contrast, the CBR model operates through a four-stage cycle (Retrieve, Reuse, Revise, and Retain) allowing it to leverage historical cases, adapt solutions to new contexts, and improve over time through continuous learning. Experimental evaluations using five benchmark datasets showed that CBR consistently outperforms traditional models across metrics including Mean Absolute Percentage Error (MAPE), accuracy, contextual adaptability, and learning efficiency. These findings validate CBR as a scalable, intelligent solution for modern cost estimation challenges. Looking ahead, future work should integrate real-time data sources, such as material price APIs and labor market feeds, to further enhance responsiveness. Natural Language Processing (NLP) techniques could extract insights from unstructured project documents, while hybrid models combining CBR with neural networks or decision trees may further improve retrieval and adaptation accuracy (Liu & Chen, 2025). Additionally, incorporating Building Information Modeling (BIM) and spatial data can enrich contextual understanding. Finally, deploying the model through a cloud-based or mobile platform would support real-time, on-site cost estimation (Fazeli et al., 2021). Collectively, these enhancements aim to make CBR not only a powerful research tool but also a practical, industry-ready solution for intelligent, adaptive cost estimation.

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Enhancing Project Governance through Case-Based Reasoning at Strategic Control Points

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ABSTRACT

Strategic control is crucial in project governance for aligning initiatives with organizational goals and enabling timely, efficient decisions. Traditional models such as Waterfall, PRINCE2, Stage-Gate, and Earned Value Management often lack adaptability in dynamic environments. This paper proposes a Case-Based Reasoning (CBR) framework that enhances governance by learning from past project experiences. The model follows four phases: Retrieval, Reuse, Revision, and Retention, allowing context-aware decisions based on historical patterns. Experiments using five datasets (PM, SP, COCOMO, JSS, OR) show that CBR achieves high case retrieval accuracy (up to 0.91), solution adaptation success (up to 0.92), governance outcome improvement (up to 36.42%), and reduced decision time (up to 23.91%). This study introduces a flexible, data-driven governance model that improves responsiveness and supports continuous learning, demonstrating CBR's potential as a transformative approach for effective decision-making in complex and uncertain project environments.

KEYWORDS: case-based reasoning, project governance, strategic control, decision-making, adaptability, project management

INTRODUCTION

One of the main problems in enhancing project governance through strategic control points s the absence of adaptive frameworks that can respond to complex, dynamic environments. Traditional governance relies on static rules, fixed milestones, and rigid controls that struggle with unexpected developments (Adedokun et al., 2025). This rigidity weakens oversight, delays risk mitigation, and reduces stakeholder alignment, especially in fast-moving digital and global contexts. Effective governance now requires real-time, context-aware, and case-specific interventions that balance compliance with innovation (Tanim and Ahmad, 2025).

Several traditional models illustrate these limitations. The Waterfall Model offers structured phases and clarity but is too rigid for rapid change (Sommerville, 2011). PRINCE2 ensures governance assurance through defined control points but risks excessive bureaucracy (Office of Government Commerce, 2009). The Stage-Gate Model aligns strategy and innovation via gate reviews but often limits responsiveness (Cooper et al., 2001). Earned Value Management integrates scope, cost, and time metrics yet lacks qualitative adaptability (Fleming and Koppelman, 2000). While valuable in certain contexts, these models fall short in experiential learning and adaptability, reducing effectiveness in uncertain project landscapes.

Case-Based Reasoning (CBR) provides an experience-driven framework to strengthen strategic control in project governance. Unlike traditional models that rely on static rules, CBR leverages historical project cases to guide decisions. At key control points (such as scope changes, resource shifts, or delays) it retrieves relevant past cases, compares contexts, and adapts proven strategies (Jaiswal and Rana, 2024). This enables rapid, context-sensitive decisions while continuously enriching the case base with new experiences to improve future interventions. By aligning historical insights with current conditions, CBR enhances adaptability, transparency, and governance resilience. It also builds stakeholder trust by ensuring evidence-based and consistent decision-making (Pradeep et al., 2024). In high-uncertainty or innovation-driven projects, CBR supports risk recognition and solution reuse, fostering agile governance.

Table 2 Traditional Model

Traditional Model	Purpose	Key Features
Waterfall Model (Balaji and Murugaiyan, 2012)	Sequential project delivery and milestone control	Linear phases, documentation-heavy, clear scope control
PRINCE2 (Joslin and Müller, 2015)	Governance and business alignment through process control	Defined roles, stage boundaries, emphasis on control points
Stage-Gate Model (Cooper, 2019)	Structured product development decision-making	Gate reviews, risk-based decision points, cross-functional assessment
Earned Value Management (Elshaer, 2013)	Quantitative tracking of project performance and variance	Cost-schedule integration, performance forecasting, variance analysis

This paper advances theory by framing CBR as a learning-based governance model and offers a practical implementation framework. The outcome is a dynamic governance toolkit that improves decision quality, enables timely interventions, and supports adaptive oversight across diverse project contexts.

RELATED WORKS

Traditional Governance Models in Project Management

Traditional project governance models like the Waterfall Model, PRINCE2, Stage-Gate, and Earned Value Management (EVM) emphasize structured processes and predefined control points to ensure project alignment, budget compliance, and risk mitigation (Adedokun et al., 2025). These models provide stability, clear accountability, and standardized documentation. As illustrated in Figure 1, PRINCE2 features defined processes such as Initiating a Project, Managing Stage Boundaries, and Controlling a Stage, reinforcing procedural control at each phase. While such structure enhances oversight, it also reflects the model's inherent rigidity and limited adaptability in dynamic project environments. However, they often struggle in dynamic, fast-paced environments where real-time decision-making and flexibility are crucial. The literature reveals a common critique of these models' rigidity, which can impede timely adaptation and stakeholder responsiveness. Researchers increasingly advocate for hybrid or adaptive models that retain control benefits while allowing contextual decision-making to improve governance effectiveness under uncertainty or innovation-driven conditions (Tettey et al., 2024).

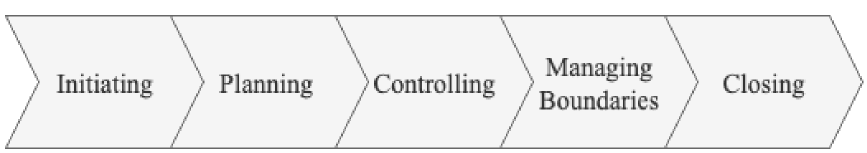

Figure 1: PRINCE2 governance process

Case-Based Reasoning in Project Management

Case-Based Reasoning (CBR) is increasingly recognized in literature as a viable model for improving decision-making in project governance. CBR systems retrieve past project cases similar to current challenges, adapt their solutions, and apply them in real-time (Feng et al., 2023). This allows for experience-driven governance at strategic control points. Studies show CBR enhances responsiveness, risk anticipation, and decision quality, especially in complex or uncertain environments. However, key challenges include case retrieval accuracy, case base maintenance, and integration with existing project management systems. Despite these limitations, CBR is praised for promoting organizational learning and adaptive governance, making it a valuable complement to traditional methods(Relich et al., 2024).

Strategic Control Points in the Project Lifecycle

Strategic control points such as planning reviews, phase transitions, scope changes, and budget checkpoints are critical junctures in the project lifecycle where governance decisions influence outcomes. The project lifecycle comprises five main sequential phases: Initiating, Planning, Executing, Monitoring and Controlling, and Closing. These stages serve as natural anchor points for embedding governance mechanisms. Literature emphasizes the role of these control points in enabling oversight, enforcing accountability, and aligning projects with strategic goals. These control points are embedded across the five stages of the project lifecycle, aligning with key phases such as planning, monitoring, and closing. Effective control point design requires a balance between procedural rigor and decision flexibility. Research also stresses the importance of contextual timing, stakeholder involvement, and data-driven insights at each control point. Optimizing these checkpoints enhances project agility, reduces failure risks, and improves stakeholder satisfaction (Thummala and Saxena, 2024). Best practices often integrate real-time dashboards, predictive analytics, and lessons learned repositories.

Digital Transformation and Intelligent Governance

Recent literature highlights how digital transformation is reshaping project governance through AI integration. Intelligent control systems (powered by Machine Learning, Case-Based Reasoning, and Expert Systems) support adaptive governance by enabling data-driven, context-aware decision-making (Paul et al., 2024). These systems monitor performance metrics, detect anomalies, and recommend interventions at strategic control points. Studies show that AI-enhanced governance improves responsiveness, reduces human error, and enables predictive risk management. However, integration challenges persist, including data quality, ethical concerns, and user trust. Nonetheless, the convergence of AI and project governance is emerging as a transformative force, offering real-time control and dynamic learning capabilities that surpass traditional governance constraints.

RESEARCH METHODOLOGY

Conceptual Model

The Case-Based Reasoning Driven Adaptive Governance Model (CBR AGM) integrates CBR into project governance by strengthening strategic control points through experiential learning. When a project situation (such as scope change, resource bottleneck, or delay) emerges, the CBR cycle begins. Relevant past cases are retrieved, adapted, and applied to the current context. Solutions may be revised with stakeholder input before implementation. New experiences are then retained in the case base, enriching future decisions. A feedback loop monitors effectiveness, reinforcing continuous learning. This model makes governance evidence-based, adaptive, and context-sensitive, improving stakeholder confidence, reducing risk, and transforming governance into a dynamic, learning-oriented system.

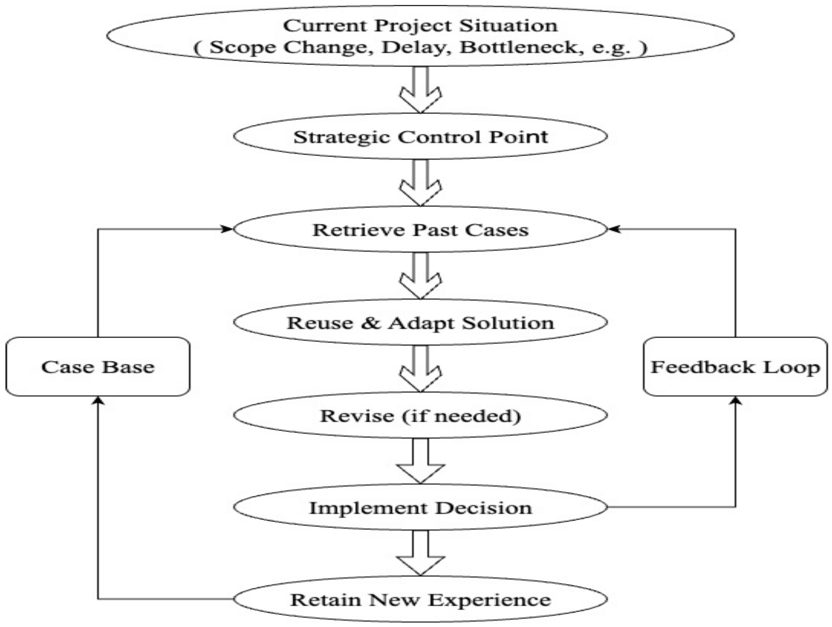

Figure 2: CBR AGM Model

Algorithm

The Case-Based Reasoning Adaptive Governance Model (CBR AGM) algorithm facilitates intelligent decision-making at strategic control points in project governance by systematically leveraging historical project knowledge. To improve clarity and maintain modular structure, the algorithm is organized into a main decision function supported by four specialized sub-functions: control point detection, case retrieval, solution adaptation, and experience retention. This format ensures continuous learning, contextual responsiveness, and operational transparency in governance execution.

Main Function: CBR Governance Decision

Function CBR Governance Decision(CPS, CB):

(i) IF Detect SCP(CPS) = False THEN
RETURN No_Action, CB

(ii) Retrieved Cases ← Retrieve Cases(CPS, CB)

(iii) Candidate Solution←Reuse Revise Solution(Retrieved Cases, CPS)

(iv) GD ← Candidate Solution

(v) Execute GD at the current strategic control point

Evaluation

1. Case Retrieval Accuracy (CRA): Measures how accurately the system retrieves the most relevant past cases based on similarity.

$$CRA = \frac{|RR_c|}{|TR_c|} \qquad (1)$$

Where RR_c is number of correctly matched cases and TR_c is number of all cases retrieved.

2. Solution Adaptation Success Rate (SASR): Evaluates the success rate of adapted solutions applied to current strategic control points.

$$SASR = \frac{|S_A|}{|T_A|} \qquad (2)$$

Where S_A is adapted solutions that resulted in effective governance and T_A is all applied adapted solutions.

3. Decision Implementation Time Reduction (DITR): Quantifies the reduction in time to make governance decisions due to CBR assistance.

$$DITR = \frac{T_0 - T_{CBR}}{T_0} \times 100\% \qquad (3)$$

Where T_0 is average time using traditional decision-making and T_{CBR} is average time using CBR model.

4. Governance Outcome Improvement (GOI): Assesses the degree of improvement in project outcomes after using CBR at control points.

$$GOI = \frac{S_{post} - S_{pre}}{S_{pre}} \times 100\% \qquad (4)$$

Where S_{pre} is outcome score before applying CBR (e.g., success rate, cost adherence) and S_{post} is outcome score after CBR implementation.

The integration of the Case-Based Reasoning Adaptive Governance Model (CBR AGM) into project governance is essential in today's complex and unpredictable environments. Traditional models rely on rigid rules, fixed milestones, and static processes, which fall short when rapid, context-aware decisions are needed. CBR enables project managers to make informed decisions by learning from historical cases, adapting proven solutions, and updating knowledge continuously. This enhances responsiveness, supports ongoing improvement, and builds stakeholder confidence through faster, evidence-based strategies. Its ability to adapt, learn from past mistakes, and respond in real-time makes CBR a powerful tool for strategic control, offering a dynamic alternative as project risks and demands evolve.

Data source

The selected datasets from the UCI Machine Learning Repository provide valuable resources for applying Case-Based Reasoning (CBR) in project governance and decision-making. Each dataset represents real-world cases that can be reused, adapted, and learned from to solve similar future problems. Table II, the Student Performance and COCOMO datasets support effort estimation and planning, while the Job Shop Scheduling and Online Retail datasets help optimize resource allocation and timing. By structuring historical data as cases, CBR can retrieve relevant patterns and improve decision quality at strategic control points. These datasets enable adaptive governance and learning-based interventions in complex project environments.

Table 2 Data source

Dataset Name	Domain	CBR Application	Key Features
Project Management Dataset (PM) (Margita et al., 2025)	Project Time & Cost Estimation	Retrieve similar project cases for effort, cost, and scope forecasting	Project type, duration, cost,resources
Student Performance Dataset (Dixit et al., 2022)	Education/Governance	Adapt strategies for educational governance and project-based learning	Grades, study time, absences, parental background

Dataset Name	Domain	CBR Application	Key Features
Software Development Effort (COCOMO) (Mansoor et al., 2024)	Software Project Estimation	Estimate resources/time for software projects based on past efforts	Code size, team experience, product complexity
Job Shop Scheduling Problem Dataset (Gui & Zhang, 2025) (Reijnen et al., 2023)	Scheduling & Resource Planning	Retrieve optimal schedules for milestone and task planning	Job ID, duration, start/end times, machine assignment
Online Retail Dataset (Turkmen, 2022)	E-Commerce Project Insights	Derive patterns for customer project targeting or release timing	Invoice ID, product, date, customer location

RESULTS AND DISCUSSION

The comparative results in Tables 3–6 highlight the superior performance of Case-Based Reasoning (CBR) in both project governance and building cost estimation. In governance evaluation, CBR consistently outperforms traditional models such as Waterfall, PRINCE2, Stage-Gate, and EVM. Table 3 shows CBR achieving the highest case retrieval accuracy (0.85–0.91) versus below 0.70 for others. Table 4 reports solution adaptation success rates of 0.86–0.92, far exceeding rigid traditional approaches. In Table 5, CBR reduces decision implementation time by 19.26%–23.91%, compared to marginal improvements or none in WD. Finally, Table 6 shows governance outcome improvements of 28.96%–36.42%, confirming CBR's adaptive intelligence, faster decision-making, and stronger results across all dimensions.

In cost estimation evaluation, CBR again delivers the best performance. Table 3 reports the lowest MAPE (7.2%–9.7%) compared with Regression (9.8%–12.4%) and Quantity Surveying (up to 16.1%). Table IV shows the highest accuracy (90.0%–94.1%), surpassing Regression (86.0%–90.2%). Table 5 demonstrates adaptability scores of 4.8–5.0, much higher than other models (<3.0). Table 6 confirms CBR's learning efficiency with 10%–14% gains, while traditional models show minimal or no improvement. Overall, the results establish CBR as the most accurate, adaptive, and learning-oriented model, making it the most effective approach for both governance and construction cost estimation.

Table 3 Case Retrieval Accuracy

Dataset	WD	P2	SGM	EVM	CBR
PM	0.58	0.61	0.65	0.68	**0.87**
SP	0.55	0.6	0.62	0.63	**0.89**
COCOMO	0.60	0.64	0.66	0.70	**0.91**
JSS	0.52	0.58	0.6	0.63	**0.85**
OR	0.57	0.59	0.61	0.65	**0.88**

Table 4 Solution Adaptation Success Rate

Dataset	WD	P2	SGM	EVM	CBR
PM	0.54	0.60	0.63	0.68	**0.90**
SP	0.51	0.56	0.58	0.61	**0.88**
COCOMO	0.56	0.63	0.66	0.69	**0.92**
JSS	0.48	0.52	0.56	0.60	**0.86**
OR	0.5	0.54	0.59	0.62	**0.89**

Table 5 Decision Implementation Time Reduction

Dataset	WD	P2	SGM	EVM	CBR
PM	0.00%	3.15%	5.42%	6.37%	**21.78%**
SP	0.00%	4.08%	6.24%	7.15%	**20.63%**
COCOMO	0.00%	2.94%	4.53%	5.68%	**23.91%**
JSS	0.00%	3.34%	5.07%	6.26%	**19.26%**
OR	0.00%	3.11%	4.69%	5.87%	**21.34%**

Table 6 Governance Outcome Improvement

Dataset	WD	P2	SGM	EVM	CBR
PM	8.24%	11.36%	14.59%	16.73%	**33.18%**
SP	7.41%	10.17%	12.86%	15.24%	**30.77%**
COCOMO	9.32%	12.68%	15.87%	18.35%	**36.42%**
JSS	6.58%	9.47%	12.35%	13.92%	**28.96%**
OR	7.28%	10.09%	13.18%	15.36%	**31.82%**

CONCLUSION

The comparative analysis in Tables 3–6 shows that Case-Based Reasoning (CBR) significantly outperforms traditional governance models in project management across multiple dimensions. Unlike structured but rigid approaches such as Waterfall, PRINCE2, Stage-Gate, and Earned Value Management, CBR demonstrates exceptional adaptability by learning from past cases to handle dynamic and complex scenarios. It achieves the highest case retrieval accuracy (up to 0.91), superior solution adaptation success rates (up to 0.92), and the greatest reduction in decision implementation time (up to 23.91%). Moreover, CBR delivers the most substantial governance outcome improvements, reaching 36.42%. These findings confirm CBR's ability to enable responsive, intelligent decision-making that aligns with evolving project needs. While traditional models ensure stability and control, their lack of flexibility limits effectiveness in fast-changing environments. In contrast, CBR accelerates decision-making, enhances adaptability, and improves outcomes, making it a superior governance approach.

Future research should expand CBR applications across industries and real-time environments. Integration with emerging technologies such as machine learning, natural language processing, and predictive analytics could enhance case matching precision and scalability. Hybrid governance models that combine CBR with structured methods like PRINCE2 or EVM may balance stability with experiential learning (Mirzaei et al., 2025). Building domain-specific case libraries will further support sector customization, particularly in healthcare, infrastructure, and software engineering. Additionally, studies should assess the long-term impact of CBR on organizational learning, agility, and stakeholder satisfaction. Finally, embedding CBR in cloud-based platforms can enable real-time decision-making and knowledge sharing across distributed teams, reinforcing its role as a transformative governance tool.

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The Impact of Short Baking Videos on Consumers' Purchase Intentions in the Digital Economy

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ABSTRACT

This study applies the Stimulus–Organism–Response (SOR) model and the dual-value framework to examine how sensory appeal and social interactivity in baking-related short videos influence consumers' purchase intentions. Survey data from 201 valid respondents were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicate that sensory appeal indirectly influences purchase intention via perceived hedonic value, while social interactivity both enhances perceived utilitarian value and directly drives purchase intention. Utilitarian value exerts a greater effect than hedonic value, underscoring practical utility as a key driver of content that combines functionality and enjoyment. These findings extend the SOR model's application to short-form video marketing and provide actionable guidance for integrating aesthetic appeal with interactive, informative features. Limitations include the China-only sample and a category-specific focus, suggesting that future research should be conducted across broader regions and product contexts.

KEYWORDS: Short-form video, Baking videos, SOR model, Hedonic value, Utilitarian value, Purchase intention

INTRODUCTION

The rapid rise of mobile internet and smart devices has fueled the growth of short-form video platforms such as Douyin, BiliBili, TikTok, and Instagram. As of June 2024, China's internet population reached 1.079 billion, with 1.04 billion users regularly consuming short videos—accounting for 96.4% of all internet users (China Internet Network Information Center, 2024). With their fast-paced, engaging nature, short videos have become a dominant medium for entertainment, information sharing, and digital marketing.

Meanwhile, China's baking industry is also experiencing robust growth. In 2023, the market reached RMB 412.3 billion (approximately USD 56.8 billion), with an average annual growth rate of 8.3% over the past five years (Huaon Industrial Research Institute, 2024). Baking-related short videos that combine aesthetic appeal with hands-on instruction are increasingly favored by consumers and are emerging as a vehicle for marketing food content.

Previous research grounded in the Stimulus–Organism–Response (SOR) framework suggests that media features like vivid visuals and interactivity can influence internal consumer states—such as perceived value, trust, and immersion—thereby affecting purchase intention (Shi et al., 2023; Yu et al., 2024)The dual-value framework distinguishes between hedonic value (pleasure, enjoyment) and utilitarian value (functionality, usefulness), both of which are critical drivers of consumer behavior (Babin et al., 1994; Luo et al., 2025). In short video content, sensory appeal (SA) is known to enhance hedonic value, while social interactivity (SI) improves utilitarian value, together influencing consumers' purchase intention (Shen & Wang, 2024).

However, existing studies often focus on categories such as fashion or electronics, with little empirical attention to hybrid content such as baking videos. These videos uniquely blend emotional satisfaction and practical utility, yet their underlying value mechanisms and behavioral impacts remain underexplored.

This study addresses the gap by integrating the SOR model and dual-value perspective to investigate how SA and SI in baking-related short videos affect consumers' purchase intentions. A structural model is proposed to test six hypotheses via PLS-SEM, with perceived hedonic and utilitarian value modeled as mediators.

This research contributes by extending the SOR framework into a hybrid, food-specific digital context; empirically validating dual-value pathways in short video marketing; and providing practical insights for marketers aiming to design emotionally engaging yet informative baking content.

LITERATURE REVIEW

Short-form video has rapidly become a dominant vehicle for product discovery and impulse buying in China's digital economy. In social commerce contexts, short video content compresses message delivery, blends entertainment with information, and enables creator–audience interaction, jointly shaping value perceptions and purchase intentions. Recent studies indicate that the practicality, manageability, and entertainment value of content can enhance consumers' trust in videos, thereby increasing their willingness to purchase. This demonstrates that value formation mechanisms and relational mechanisms play a significant role in short-video scenarios. (Liu & Wang, 2023; Wu & Zhang, 2024).

The SOR lens and the dual-value pathway

This study adopts the Stimulus–Organism–Response (SOR) paradigm: platform/content features act as stimuli; internal organismic states—such as perceived value, flow/immersion, social presence, and trust—serve as the organism; and purchase intention is the response. In short-video contexts, large-sample studies repeatedly validate SOR pathways in which interaction and platform qualities influence perceived value/immersion that, in turn, affect purchase-related outcomes. For example, Hewei (2022) found that media interactivity in mobile short-video apps positively influences perceived value and immersion experience, both of which subsequently enhance purchase intention(Hewei, 2022). Similarly, Yu et al. (2024) applied an extended SOR framework to furniture-related short-video advertisements. They revealed that stimuli such as perceived entertainment value, media richness, and convenience significantly drive flow and telepresence (organismic states), leading to stronger purchase intentions (Yu et al., 2024). Within the organismic layer, consumers commonly form hedonic value (enjoyment, fun) and utilitarian value (usefulness, efficiency). The classic dual-value framework remains foundational for distinguishing affective pleasure from instrumental value and for measuring both in a single consumption episode—especially pertinent when content is simultaneously sensory-rich and instructive, as many short videos are (Babin et al., 1994).

From external cues to internal value: content and interactivity

Two feature families align directly with the present model. Sensory appeal (SA)—the vividness of visuals, sound, pacing, and editing—typically elevates perceived hedonic value (PH) by enriching the affective experience (e.g., color, texture, plating, ASMR-like sounds). Social interactivity (SI)—commenting, replying, @-mentions, and timely creator responses—improves diagnosticity, clarifies steps, and reduces ambiguity, thereby enhancing perceived utility (PU). Empirical SOR research shows that interaction and platform qualities (information, system, and service) significantly enhance user experience and value assessments, which then elevate purchase-related outcomes. For instance, sensory-rich marketing cues have been shown to influence consumer emotions, judgment, and behavior, reinforcing hedonic value (Krishna, 2012). Meanwhile, social media affordances—like commenting and meta-voicing—have been empirically linked to enhanced perceived utilitarian value and user engagement in short video contexts (Ma et al., 2025). More recent findings indicate that persona perception and social presence amplify this pathway—interpersonal cues can strengthen the conversion of content/interactivity into value and, ultimately, intention (Shen & Wang, 2024). Complementarily, trust often mediates the effect of content attributes (usefulness, ease, entertainment) on purchase intention in short-video commerce (Luo et al., 2025). Taken together, these results justify modeling PH/PU as mediators between SA/SI and PI.

Baking short videos are a fitting context

On Chinese social platforms, accumulating evidence indicates that perceived usefulness, ease, and entertainment not only directly predict purchase intention but also do so indirectly through trust. Persona perception and social presence further strengthen the transmission from content/interaction to intention. For example, Syaharani and Yasa (2022) highlight how perceived usefulness and ease of use influence repurchase intention via trust mediation (Syaharani & Yasa, 2022). Methodologically, prediction-oriented studies with multiple latent constructs frequently adopt PLS-SEM and report reliability (α, CR), convergent validity (AVE), discriminant validity (preferably HTMT), and structural diagnostics (VIF, R^2, Q^2, f^2) in accordance with best-practice guidance (Hair et al., 2019). This aligns with the present study's aim to explain value-formation routes from SA/SI to PI.

RESEARCH METHODOLOGY

Two feature families align directly with the present model. Sensory appeal (SA)—the vividness of visuals, sound, pacing, and editing—typically elevates perceived hedonic value (PH) by enriching the affective experience (e.g., color, texture, plating, ASMR-like sounds). Social interactivity (SI)—commenting, replying, @-mentions, and timely creator responses—improves diagnosticity, clarifies steps, and reduces ambiguity, thereby enhancing perceived utility (PU). Empirical SOR research shows that interaction and platform qualities (information, system, and service) significantly enhance user experience and value assessments, which then elevate purchase-related outcomes. More recent findings indicate that persona perception and social presence amplify this pathway—interpersonal cues can strengthen the conversion of content/interactivity into value and, ultimately, intention (Shen & Wang, 2024). Complementarily, trust often mediates the effect of content attributes (usefulness, ease, entertainment) on purchase intention in short-video commerce (Luo et al., 2025). Taken together, these results justify modeling PH/PU as mediators between SA/SI and PI.

Theory and Hypotheses

Grounded in existing research on short video marketing and consumer behavior, six hypotheses were proposed:

H1a: SA positively influences PH.
H1b: SA positively influences PI.
H2a: SI positively influences PU.
H2b: SI positively influences PI.
H3: PH positively influences PI.
H4: PU positively influences PI.

H5 and H6 examine the mediating roles of PH and PU between SA/SI and PI, aligning with prior findings that perceived hedonic and utilitarian values can transmit the effects of content features to purchase intentions (Babin et al., 1994; Luo et al., 2025; Shen & Wang, 2024).

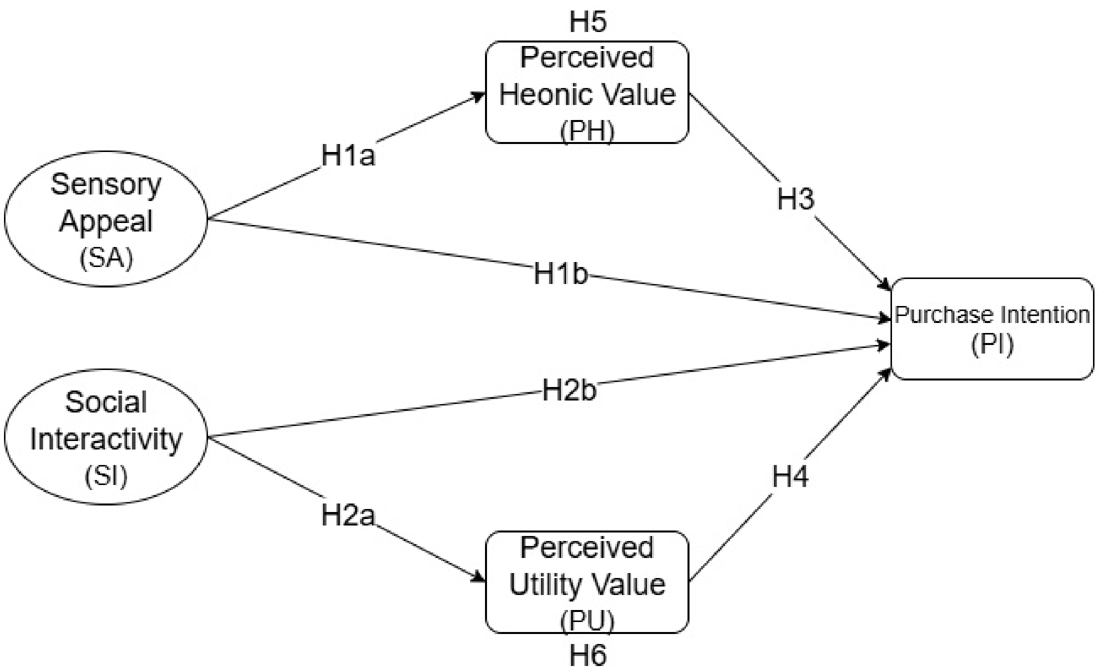

Figure 2: Research model diagram

Data Collection

I Data were collected through an online questionnaire distributed via Credamo (https://www.credamo.com), a widely used academic survey platform in China. A convenience sampling method targeted participants who had watched and commented on baking-related short videos within the past six months. In total, 270 questionnaires were distributed, and 201 valid responses were retained after screening. A questionnaire was considered valid if all questions were completed, the response time exceeded 180 seconds, and no more than seven consecutive identical responses were recorded. Participants received a 1 RMB monetary incentive for completing the study.

To ensure adequate statistical power, an a priori power analysis was conducted using G*Power 3.1 (Faul et al., 2009) with the following parameters: medium effect size ($f^2 = 0.15$), significance level ($\alpha = 0.05$), statistical power ($1 - \beta = 0.95$), and five predictors (the maximum number of arrows pointing to PI in the model). The results indicated a minimum required sample size of 74, which is far below our actual valid sample of 201. This confirms that the dataset meets the statistical requirements for the proposed structural equation model.

Data Analysis

This study employed Smart-PLS software to conduct partial least squares structural equation modelling (PLS-SEM). I selected this method because it is suitable for studies with small sample sizes and can handle complex models involving multiple latent constructs. This analysis consists of two steps: First, evaluate whether the measurement model meets standards in terms of reliability, internal consistency, convergent validity, and discriminant validity. Second, evaluating the structural model through collinearity checks (VIF), explanatory power (R^2), predictive relevance (Q^2), and path coefficient significance using bootstrapping. Measurement model criteria and thresholds followed Hair et al. (2019), while discriminant validity was assessed using the HTMT criterion (< 0.85) proposed by Henseler, Ringle, and Sarstedt (2015).

RESEARCH RESULTS

Descriptive Statistics

A total of 270 questionnaires were distributed via the Credamo platform, and 201 valid responses meeting the inclusion criteria were included in the analysis. The sample comprised participants who had watched and commented on baking-related short videos within the past six months. The demographic composition included diverse age groups and educational backgrounds, providing a representative view of the target audience for baking video marketing.

Measurement Model Assessment

In this study, the reliability and validity metrics met established thresholds for exploratory research. Cronbach's alpha values ranged from 0.614 to 0.731, exceeding the minimum criterion of 0.60 recommended for exploratory work. Composite reliability values ranged from 0.792 to 0.829, exceeding the commonly accepted 0.70 threshold. Average Variance Extracted (AVE) values ranged from 0.552 to 0.605, all above the 0.50 benchmark, thus supporting convergent validity. Discriminant validity was confirmed through both the Fornell–Larcker criterion and the Heterotrait–Monotrait ratio (HTMT), with all HTMT values below 0.85.

These thresholds and evaluation criteria are drawn from prior methodological literature, including Hair et al. (2014), Hair et al. (2019), Cheung and Wang, and Henseler et al. (2015).

Although the outer loadings of SA1 (0.675) and SI1 (0.619) are slightly below the recommended threshold of 0.70, they were retained due to theoretical importance and minimal impact on CR and AVE after deletion.

Table 1 Reliability and Convergent Validity Measurements

Construct	Code	Out Loading	Cronbach alpha	Composite Reliability	AVE
Sensory Appeal	SA1	0.675	0.614	0.792	0.561
	SA2	0.763			
	SA3	0.804			
Social Interactivity	SI1	0.619	0.731	0.829	0.552
	SI2	0.676			
	SI3	0.821			
	SI4	0.834			
Perceived Hedonic Value	PH1	0.763	0.674	0.821	0.605

Construct	Code	Out Loading	Cronbach alpha	Composite Reliability	AVE
	PH2	0.803			
	PH3	0.767			
	PU1	0.643			
Perceived Utility value	PU2	0.752	0.744	0.836	0.563
	PU3	0.851			
	PU4	0.741			
	PI1	0.7			
Purchase Intention	PI2	0.794	0.746	0.838	0.5[1]65
	PI3	0.727			
	PI4	0.783			

Discriminant validity was established through both Table 2, the Fornell–Larcker criterion, and Table 3, the Heterotrait–Monotrait (HTMT) ratio. In the Fornell–Larcker matrix, the square root of each construct's AVE exceeded its correlations with other constructs (e.g., PH=0.778 > correlations with other variables). All HTMT ratios were below the conservative threshold of 0.85, supporting discriminant validity.

Table 2 Fornell Larcker

	PH	PI	PU	SA	SI
PH					
PI	0.555				
PU	0.541	0.619			
SA	0.792	0.393	0.46		
SI	0.54	0.703	0.545	0.522	

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Table 3 Heterotrait-Monotrait(HTMT) Ratio

	PH	PI	PU	SA	SI
PH					
PI	0.555				
PU	0.541	0.619			
SA	0.792	0.393	0.46		
SI	0.54	0.703	0.545	0.522	

Structural Model Assessment

The collinearity diagnosis revealed that all variance inflation factors (VIF) were below the 3 threshold, indicating no multicollinearity issues. The path coefficients, t-values, and p-values from the hypothesis tests are summarized in Table 4.

H1a (SA → PH): Significant positive effect (β=0.525, t=9.845, p<0.001), indicating that stronger sensory appeal in baking videos increases perceived hedonic value.

H1b (SA → PI): Non-significant effect (β=-0.037, t=0.426, p=0.67), suggesting sensory appeal alone does not directly influence purchase intention.

H2a (SI → PU): Significant positive effect (β=0.431, t=6.591, p<0.001), showing that social interactivity strongly enhances perceived utility value.

H2b, H3, H4, H5, H6: Additional paths (e.g., from SI to PI, PH to PI, and PU to PI) also tested, with varying significance levels reflecting the complex interplay between value perceptions and purchase intention.

All inner VIFs were below 3. Indirect effects were significant for SA→PH→PI (β=0.090, BCA 95%CI [0.003, 0.170]) and SI→PU→PI (β=0.121, BCA 95%CI [0.054, 0.207]); VAF values indicated partial mediation. Effect sizes (f^2) showed medium impact for SA→PH and small-to-medium for PU/PH→PI.

Table 4 Path Coefficients and Hypothesis Testing Results

Hypothesis	Path	Beta Coefficient	Std. DEV	t-value	p-value		95% CI	Supported
Direct effects								
H1a	SA → PH	0.525	0.053	9.845	0.000	***	[0.421,0.631]	Yes
H1b	SA → PI	-0.037	0.086	0.426	0.670		[-0.195,0.14]	No
H2a	SI → PU	0.431	0.065	6.591	0.000	***	[0.31,0.569]	Yes
H2b	SI → PI	0.372	0.087	4.272	0.000	***	[0.189,0.529]	Yes
H3	PH → PI	0.171	0.08	2.127	0.033		[0.005,0.318]	Yes
H4	PU → PI	0.28	0.078	3.563	0.000	***	[0.126,0.432]	Yes

Hypothesis	Path	Beta Coefficient	Std. DEV	t-value	p-value		95% CI	Supported
Mediating effects								
H5	SA -> PH -> PI	0.09	0.042	2.135	0.033	*	[0.003,0.170]	Yes
H6	SI -> PU -> PI	0.121	0.039	3.067	0.002	**	[0.054,0.207]	Yes

Note: *** $p < 0.001$,** $p < 0.01$, * $p < 0.05$

The R^2 value for Purchase Intention was 0.399, indicating moderate explanatory power, while Perceived Hedonic Value and Perceived Utility Value had R^2 values of 0.186 and 0.431, respectively, reflecting their dependence on SA and SI. Q^2 values for endogenous constructs were all above zero (PI=0.268, PH=0.16), confirming predictive relevance. Effect size (f^2) analysis showed that SA had a medium effect on PH ($f^2 = 0.097$) and SI had a notable effect on PU.

Summary of Findings

The results show that sensory appeal in baking short videos significantly shapes consumers' hedonic perceptions, which in turn mediate rather than directly drive purchase intentions. In contrast, social interactivity not only strengthens perceived utility but also plays a critical role in shaping behavioral intentions through value perceptions. These findings underscore the importance of designing baking video content that blends aesthetic sensory elements with interactive and informative features to maximize both enjoyment and perceived usefulness, thereby enhancing consumer purchase intentions.

DISCUSSION

This study examined how sensory appeal (SA) and social interactivity (SI) in baking short videos influence consumers' purchase intentions (PI) through perceived hedonic (PH) and utilitarian (PU) values, grounded in the SOR framework (Babin et al., 1994; Luo et al., 2025). The findings offer both theoretical and practical insights into short video marketing in social commerce.

First, SA significantly enhanced PH (H1a), supporting prior research that vivid audiovisual cues enrich consumers' affective experiences and heighten hedonic value (Luo et al., 2025; Shi et al., 2023). However, SA did not directly influence PI (H1b), aligning with studies suggesting that sensory richness must translate into value perceptions before affecting behavioral outcomes (Luo et al., 2025). This indicates that visual and auditory appeal in baking videos is impactful mainly through emotional enjoyment rather than immediate purchase triggers.

Second, SI positively influenced PU (H2a) and PI (H2b), consistent with evidence that interactive features improve perceived utility and reduce uncertainty (Shen & Wang, 2024; Venkatesh et al., 2003). This underscores the importance of responsive communication, comments, and creator–viewer engagement for converting interest into purchase intention.

Third, both PH (H3) and PU (H4) significantly predicted PI, confirming that consumers' intentions are shaped by a blend of enjoyment and practical benefits (Babin et al., 1994). PU's stronger coefficient suggests that practical value may weigh more heavily in purchase decisions, especially in contexts like baking, where clear instructions and perceived usefulness matter.

Moreover, mediation tests supported H5 and H6: PH partially mediated the SA–PI relationship, while PU mediated the SI–PI link. This mirrors findings in digital marketing literature that content features influence behavior mainly through internal value perceptions (Luo et al., 2025; Shen & Wang, 2024).

Theoretically, these results reinforce the SOR model's applicability to short-form video commerce and extend dual-value theory to a context combining hedonic enjoyment and instructional utility. They also echo technology adoption patterns in other domains, where perceived usefulness is often a stronger driver than ease of use (Venkatesh et al., 2003).

Practically, marketers should design baking videos that integrate aesthetic richness with interactive, informative features to optimize both PH and PU. Sensory appeal can draw attention, but structured interactivity and clear utility may be the decisive factors for purchase. Content strategies blend emotional engagement with actionable guidance, leveraging comments, Q&A, and creator presence to enhance trust and value perception.

CONCLUSION

Grounded in the SOR model and the dual-value framework, this study investigated how sensory appeal and social interactivity in baking-related short videos affect consumers' purchase intentions. Results show that sensory appeal influences purchase intention mainly indirectly through perceived hedonic value, while social interactivity enhances perceived utilitarian value and also directly promotes purchase intention. The stronger role of utilitarian value suggests that, in content that combines functionality and enjoyment, practical utility may be the key driver.

Echoing the first study's emphasis on performance expectancy, this research highlights the mediating role of value perceptions within the stimulus–response chain. These findings extend the application of the SOR model in short-form video marketing and support the dual-value framework in contexts where emotional engagement and practical guidance coexist.

However, limitations remain. The sample was limited to users who had recently viewed and commented on baking-related short videos, and all data were collected in China, which may affect generalizability. Future studies could expand to different regions and product categories, and include variables such as trust and immersion to enhance the model's explanatory power.

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