



# An artificial intelligence-enabled strategy artefact for digital gold ecosystems: A design science study

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Received Date: 10 February, 2026

Revised Date: 26 May, 2026

Accepted Date: 19 August, 2026

## ABSTRACT

**Background:** Digital financial ecosystems generate high-volume, heterogeneous, and fast-moving behavioral data, yet many firms still lack a coherent strategic mechanism for converting these signals into timely, governable, and value-creating decisions. This study aimed to design and evaluate an artificial intelligence-enabled strategy artifact for digital gold ecosystems that operationalizes algorithmic sensing, seizing, and reconfiguring to support customer engagement prediction, product uptake orchestration, and repayment risk anticipation. **Methods:** The study employed design science research and proceeded through iterative problem identification, artifact specification, architecture development, proof-of-concept demonstration, and performance evaluation. A multimodal data configuration combining transaction-like records, behavioral event sequences, complaint-text signals, and market context variables was used to test the artifact under realistic digital ecosystem conditions. **Findings:** The findings showed that the artifact produced an integrated decision architecture with stronger predictive, strategic, and governance capabilities than conventional isolated models and rule-based approaches. **Conclusion:** In conclusion, the artifact provides transferable design knowledge for digital financial strategy. Policy recommendations include strengthening data governance, explainability, fairness auditing, and institutional readiness for responsible artificial intelligence deployment. **Novelty/Originality of this article:** This novelty lies in translating dynamic capabilities into algorithmic routines embedded in a governable strategic system rather than a standalone predictive model.

**KEYWORDS:** algorithmic capabilities; design science research; digital gold ecosystem; financial services; strategic artifact.

## 1. Introduction

The dramatic shift toward the digitalization of financial services has fundamentally redefined the mechanisms through which value is created, captured, and governed within modern business ecosystems (Gurbaxani, 2023; Zakir et al., 2023). Digital platforms are no longer merely intermediaries; they have matured into sophisticated, data-intensive infrastructures (Oztas et al., 2024; Tamara et al., 2023). These systems continuously generate a high-volume, high-velocity, and high-variety stream of information through customer interactions, transactional flows, and complex algorithmic processes. This structural transformation has moved the core of strategic decision-making away from episodic, human-centered analysis toward increasingly automated, real-time, data-driven systems that actively determine organizational outcomes (Fast et al., 2023; Hundekari et al.,

### Cite This Article:

Hutabarat, J. S., & Hamise, V. T. (2026). An artificial intelligence-enabled strategy artefact for digital gold ecosystems: A design science study. *Journal of Entrepreneurial Economics*, 3(2), 156–176. <https://doi.org/10.61511/jane.v3i2.2026.3401>

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2025). Consequently, firms operating within these digital financial ecosystems encounter unprecedented opportunities alongside escalating complexity when attempting to translate raw data into actionable, governable, and strategically aligned decisions (Al Firdausi & Kurniawan, 2025; Zakir et al., 2023).

Within this broader landscape, asset-backed services represent a particularly significant and strategically dense domain (Brody & Pureswaran, 2015; Liu et al., 2025). Digital gold ecosystems serve as a primary example of this complexity by integrating multiple layers of financial functionality, including investment, savings, collateralized lending, and liquidity management within a single, unified digital interface (Gurbaxani, 2023; Sujit et al., 2025). Users do not interact with these platforms in a vacuum; they participate simultaneously as investors, borrowers, and service recipients. This multifaceted engagement generates heterogeneous behavioral traces that reflect varying levels of intensity, financial intent, risk exposure, and experiential feedback. These ecosystems produce rich, multimodal data streams encompassing transactional logs, clickstream patterns, repayment sequences, and unstructured narratives from customer complaints, which collectively offer a granular, high-fidelity representation of dynamic and uncertain environments (Meier et al., 2023; Piccialli, 2022).

In emerging markets, particularly within Indonesia and the wider Southeast Asian region, digital gold services have attained strategic prominence due to their role in bridging financial inclusion and enabling flexible, asset-based financing (Gurbaxani, 2023; Tamara et al., 2023). Institutions such as PT Pegadaian have successfully expanded digital gold and pawn services to satisfy the rising demand for accessible investment and short-term liquidity solutions (Rosiyani & Hasyim, 2021; Sujit et al., 2025). The widespread adoption of mobile-based financial platforms has amplified the scale and diversity of the data generated within these systems, creating fertile ground for data-driven strategy (Fast et al., 2023; Tamara et al., 2023). However, the mere abundance of data does not automatically result in strategic clarity. Organizations frequently struggle to convert high-frequency, heterogeneous data into timely decisions that are not only predictive but also explainable, auditable, and strictly aligned with rigorous regulatory frameworks.

Existing academic discourse has long recognized the strategic importance of big data analytics and artificial intelligence in facilitating data-driven decision-making (Piccialli, 2022; Talaoui et al., 2023). Significant evidence suggests that big data analytics capability is positively associated with firm performance, strategic agility, and innovation (Hundekari et al., 2025; Mikalef & Gupta, 2021). Similarly, work regarding artificial intelligence capability has highlighted its potential to enhance organizational creativity, operational efficiency, and the overall quality of decisions. Despite these theoretical advances, much of the prior work treats analytics and artificial intelligence as abstract organizational resources or capabilities rather than as explicitly designed systems embedded directly within decision-making processes (Hevner et al., 2004). This limited perspective hinders the development of actionable guidance on how predictive insights can be systematically translated into strategic actions within complex, multi-layered ecosystems.

Furthermore, a substantial portion of the financial analytics literature remains preoccupied with isolated predictive tasks, such as credit scoring, fraud detection, or customer segmentation (Julaiti et al., 2026; Shahana et al., 2023). While these specific applications have achieved a high degree of methodological sophistication, they are typically implemented as standalone models that operate independently of broader strategic objectives. As a result, the output of these models often remains disconnected from actual decision execution, governance mechanisms, and ecosystem-level orchestration (Alotaibi, 2025; Vaia et al., 2022). This fragmentation is especially problematic in digital gold ecosystems, where engagement behavior, product uptake, and repayment risk are deeply interdependent and evolve dynamically over time (Al Firdausi & Kurniawan, 2025). The absence of integrated frameworks that bridge the gap between multimodal analytics, decision translation, and governance creates a critical disconnect between raw analytical capability and actual strategic impact.

From a theoretical standpoint, dominant frameworks in strategic management such as the resource-based view and the theory of dynamic capabilities provide essential insights into how firms achieve competitive advantage (Teece, 2007; Tolin & Piccaluga, 2024). The theory of dynamic capabilities defines organizational success as the ability to sense opportunities, seize them through precise resource allocation, and reconfigure capabilities in response to environmental shifts (Eisenhardt & Martin, 2017; Ellström et al., 2022). However, these frameworks were originally developed in contexts characterized by lower data frequency and predominantly human-driven decision-making. Consequently, they offer insufficient operational guidance for modern environments where sensing, seizing, and reconfiguring are increasingly mediated by algorithmic systems that process large-scale, real-time data streams (Nikolaev, 2021).

Recent inquiries have begun to explore the intersection of artificial intelligence, big data, and strategy, emphasizing the necessity of integrating analytical capabilities into the heart of strategic decision-making (Mikalef & Gupta, 2021; Talaoui et al., 2023). Nevertheless, a significant limitation persists: existing studies rarely specify how these capabilities can be deliberately designed, implemented, and governed as coherent, unified systems. There is a notable lack of research that provides actionable blueprints for integrating multimodal data analytics, predictive modeling, decision translation, and governance mechanisms within a single strategic framework. In highly regulated domains such as financial services, this limitation is critical, as decision-making systems must satisfy not only performance requirements but also the highest standards of transparency, fairness, and accountability (Hundekari et al., 2025; Xia et al., 2024).

The absence of such integrated systems highlights a fundamental gap in current knowledge. While it is established that analytics and artificial intelligence are vital for strategy, there has been insufficient focus on how to design the actual systems that operate these capabilities in a way that is both strategically effective and fundamentally governable (Brody & Pureswaran, 2015; Tolin & Piccaluga, 2024). In other words, there is currently no comprehensive framework that connects behavioral data signals, predictive modeling, strategic decision rules, and governance mechanisms into a single, implementable system tailored specifically to digital financial ecosystems (Andreini et al., 2022; Imani et al., 2026). This gap becomes increasingly salient as organizations seek to move beyond isolated applications toward the full-scale orchestration of data-driven decision-making.

To address this structural disconnect, this study develops an artificial-intelligence-enabled strategy system for digital gold ecosystems. This system is conceptualized as a modular decision-support structure that operationalizes algorithmic sensing, seizing, and reconfiguring (Hundekari et al., 2025). Algorithmic sensing involves the continuous detection and interpretation of behavioral and transactional signals using multimodal data (Kumar, 2022; Seng & Ang, 2019). Algorithmic seizing refers to the translation of predictive insights into actionable interventions, such as refined customer segmentation, targeted engagement, and proactive risk mitigation (Jing, 2025). Algorithmic reconfiguring enables the dynamic adaptation of decision rules and resource allocation based on real-time performance monitoring and governance constraints.

Crucially, the proposed system extends beyond traditional predictive models by embedding decision translation and governance mechanisms directly into its core architecture. This includes the integration of explainability techniques, traceable data pipelines, and fairness monitoring to ensure that algorithmic decisions remain transparent and aligned with regulatory expectations (Haelterman, 2022). By doing so, the system bridges the gap between analytical capability and strategic execution, providing a coherent framework for managing the inherent complexity of digital gold ecosystems (Xia et al., 2024).

This study adopts a design-oriented approach, recognizing that the primary objective is not merely to explain empirical phenomena but to create and evaluate a novel system that addresses a real-world strategic problem. This methodology is particularly suitable for this context because it emphasizes the creation of systems that are both theoretically grounded and practically relevant (Peppers et al., 2007). Through iterative cycles of development and evaluation, the study refines the system to ensure its feasibility, robustness, and strategic

utility. The evaluation focuses on predictive performance, decision relevance, and governance requirements, providing a comprehensive assessment of the system's effectiveness (Peffer et al., 2007).

The inquiry is guided by several core questions: how can an artificial-intelligence-enabled strategy system be designed to integrate multimodal data and support real-time decision-making in digital gold ecosystems; to what extent can such a system translate predictive outputs into actionable strategic interventions; and how can governance mechanisms be embedded within the system to ensure transparency, fairness, and accountability. These questions reflect the dual focus on system design and evaluation, as well as the necessity of aligning analytical capabilities with both strategic and regulatory mandates.

The contributions of this study are twofold. First, it advances strategic management theory by operationalizing dynamic capabilities as algorithmic routines embedded in data-driven decision systems. By translating abstract concepts such as sensing, seizing, and reconfiguring into concrete system components, the study provides a more actionable and technologically grounded understanding of dynamic capabilities in the era of big data. Second, it contributes to practice by offering a transferable blueprint for designing and implementing strategy systems in digital financial ecosystems. This blueprint provides essential guidance on how to integrate multimodal analytics, predictive modeling, decision translation, and governance mechanisms into a coherent and scalable system.

The increasing complexity of digital financial ecosystems necessitates new approaches to strategy that transcend traditional analytical tools. The integration of big data and artificial intelligence into decision-making requires not only advanced modeling techniques but also carefully designed systems that ensure strategic relevance and governance integrity. By developing and evaluating an artificial-intelligence-enabled strategy system for digital gold ecosystems, this study responds to this critical need and provides a foundation for future research in the field of technology-driven strategic management.

## 2. Methods

### 2.1 Research methodology, strategy, and unit of analysis

This study adopts a design science research (DSR) approach, executed through a mixed-method framework that integrates conceptual architecture, computational modeling, and rigorous proof-of-concept evaluation (Peffer et al., 2007; Storey et al., 2025). The selection of DSR as the primary methodology is dictated by the specific requirements of the problem. Conventional social science methods often limit themselves to describing or explaining existing phenomena; however, this inquiry seeks to proactively design, construct, and evaluate a strategic artifact capable of resolving a persistent organizational challenge within a volatile digital financial ecosystem. The orientation of this work is therefore predominantly solution-centric, utilizing quantitative procedures to assess the utility and performance of the developed system. This positioning aligns with established traditions in information systems where the core contribution is the generation of transferable design knowledge through the iterative creation and assessment of purposeful artifacts (Gregor & Zwikael, 2024).

The research strategy is defined as a design-oriented case study supported by computational experimentation (Holopainen et al., 2020). The digital gold ecosystem serves as the broader industrial context, while the operational domain of PT Pegadaian provides the motivating organizational backdrop. Given the inherent constraints in accessing full, proprietary corporate datasets due to regulatory and confidentiality requirements, the design cycle utilizes a sophisticated configuration of public proxy data, contextually aligned financial series, and synthetic event-sequence augmentation (Storey et al., 2025). This strategy is robust and appropriate because the primary objective is to validate the internal logic of the design, its architectural feasibility, and its evaluative superiority over baseline methods, rather than to generate institution-specific causal estimates (Imbens & Kolesár,

2016; Stock & Watson, 2008). Iterative build-evaluate cycles, supported by realistic data configurations and scenario-based testing, provide a rigorous foundation for artifact evaluation in highly regulated financial environments.

The unit of analysis is structured across three distinct layers to capture the complexity of the ecosystem (Wingate et al., 2025). At the micro level, the focus is on the customer-event sequence of a temporally ordered set of behavioral, transactional, and service interactions tied to an anonymized user (Homburg et al., 2017; Orlando, 2020). At the meso level, the analysis shifts to the customer-journey episode, which integrates signals from engagement activity, product uptake, repayment behavior, and the qualitative experience of the complaint process (Dimitrova & Öhman, 2024). At the macro level, the unit of analysis is the strategy artifact itself, viewed as a modular system that transforms high-frequency multimodal signals into actionable strategic recommendations. This multi-layered approach is essential because the contribution of this study extends beyond a single predictive model; it offers a systemic link between granular customer signals and ecosystem-wide strategic decision-making.

## *2.2 Design science research framework*

The execution of this study follows the design science research methodology (DSRM), a structured sequence that facilitates the transition from problem identification to the communication of design principles (Holopainen et al., 2020; Peffers et al., 2007). The methodology progresses through six explicit stages: identifying the problem and its motivations, defining solution objectives, designing and developing the artifact, demonstrating its functionality in a proof-of-concept environment, evaluating performance against baseline criteria, and finally communicating the resulting design knowledge (Gregor & Zwikael, 2024). To enhance the traceability and coherence of this process, the DSRM is augmented by a meta-integrated analytical framework (Ladeira et al., 2024). This framework ensures that every methodological decision from the initial industry reality layer to the final higher-order knowledge abstraction layer remains tethered to the original business challenge and the intended theoretical contribution.

DSR is preferred over purely empirical or descriptive strategies for several reasons. First, the primary gap identified in current practice is the lack of a coherent system capable of simultaneously orchestrating engagement, product uptake, and risk profiling within a digital gold framework. Second, the problem is fundamentally socio-technical, requiring a purposeful arrangement of models, data flows, and strategic rules rather than a mere estimation of statistical correlations. Third, the expected output is generalizable design knowledge that can be applied across similar financial ecosystems. These characteristics make a design-oriented approach the most effective vehicle for achieving the research objectives.

## *2.3 Artifact requirements and functional specification*

The developed system is formally specified as an artificial intelligence (AI-Enabled) digital gold ecosystem strategy artifact. Its functional requirements are derived from a synthesis of the business problem and the existing body of knowledge regarding AI capabilities, big data analytics, explainable finance, and strategic agility (Ciampi et al., 2020; Sjödin et al., 2023). To be considered successful, the artifact must satisfy six core functional specifications. It must support multimodal data ingestion, allowing for the simultaneous processing of structured transactional logs, semi-structured clickstream data, and unstructured complaint narratives (Fast et al., 2023; Woerner & Wixom, 2015). It must also possess temporal intelligence to detect and exploit the sequential dependencies inherent in financial behavior.

Beyond mere prediction, the system is required to produce decision-relevant outputs. Model scores are translated into concrete strategic levers, such as targeted outreach triggers or automated risk-limit adjustments (Jose et al., 2024; Kohtamäki et al., 2025).

Furthermore, architecture must embed governance functions, including explainability and fairness diagnostics, to ensure regulatory compliance (Abraham et al., 2019). The system must be scalable and demonstrate clear superiority over traditional baseline approaches, such as standard logistic regression or static rule-based segmentation, according to predefined acceptance thresholds. These requirements ensure that the artifact addresses the high-frequency and high-variety data environment that renders conventional strategic models insufficient.

#### 2.4 Data context and dataset configuration

The proof-of-concept environment utilizes a multimodal dataset configuration comprising five distinct categories: digital transaction data (purchases, sales, and redemptions), sequential interaction data (clickstream traces), repayment data (scheduled vs. realized sequences), complaint text data (customer service narratives), and external context data (gold price volatility and macroeconomic indicators) (Tolin & Piccaluga, 2024). The consolidated corpus contains approximately 1.27 million structured event records and 38,412 unstructured text records. This data structure preserves the essential challenges of the digital gold domain, including temporal density, significant class imbalance, and cross-domain dependencies.

The data is partitioned into three levels of observation: event-level records, session-level aggregates, and customer-episode windows (Abraham et al., 2019; Xia et al., 2024). The evaluation window is organized at the daily level to ensure alignment with macroeconomic context, while behavioral predictions are executed at the session or event level (Imani et al., 2026; Seng & Ang, 2019). This granular organization allows the system to maintain a high degree of sensitivity to shifting customer behaviors while remaining grounded in broader market trends.

#### 2.5 Variable operationalization and indicator formulae

The artifact is evaluated through a rigorous set of constructed independent variables, dependent variables, and control variables. The primary independent variables are derived from behavioral signals and sequence patterns. First, the behavioral intensity index (BII). This metric represents the normalized intensity of digital activity for a given user. The BII is calculated as:

$$BII_i = w_1 SF_i + w_2 FD_i + w_3 (1 - REC_i) \quad (\text{Eq. 1})$$

where  $BII_i$  denotes the behavioral intensity index of customer  $i$ ,  $SF_i$  is normalized session frequency,  $FD_i$  is normalized funnel depth,  $REC_i$  is normalized recency, and  $w_1 + w_2 + w_3 = 1$ . Second, the gold accumulation rhythm (GAR). These variables measure the consistency and pacing of digital gold acquisition, penalizing irregular or erratic buying patterns. The GAR is calculated as below, where  $GAR_i$  represents gold accumulation rhythm,  $Buy_{it}$  is the gold purchase amount of user  $i$  at time  $t$ ,  $T$  is the observation window,  $\sigma$  is the standard deviation,  $\mu$  is the mean, and  $\epsilon$  is a small constant to prevent division by zero.

$$GAR_i = \frac{\sum_{t=1}^T Buy_{it}}{T} \times \left( 1 - \frac{\sigma(Buy_{it})}{\mu(Buy_{it}) + \epsilon} \right) \quad (\text{Eq. 2})$$

Third, the repayment irregularity coefficient (RIC). This coefficient represents the normalized deviation of actual repayments from the scheduled financial sequence. This pattern is calculated as:

$$RIC_i = \frac{1}{N_i} \sum_{N=1}^{N_i} \frac{|\Delta_{in}^{act} - \Delta_{in}^{sch}|}{\Delta_{in}^{sch} + \epsilon} \quad (\text{Eq. 3})$$

where  $RIC_i$  measures repayment irregularity,  $\Delta_{in}^{act}$  is the actual repayment interval,  $\Delta_{in}^{sch}$  is the scheduled repayment interval,  $N_i$  is the number of repayment observations, and  $\epsilon$  is a small constant. Fourth, the complaint topic severity (CTS). This variable captures the strategic impact of customer complaints by weighing topic probability against sentiment intensity. It is calculated as below, where  $CTS_i$  is complaint topic severity,  $p_{ik}$  is the probability that complaint  $i$  belongs to topic  $k$ ,  $s_{ik}$  is sentiment intensity, and  $\omega_k$  is the strategic weight assigned to topic  $k$ .

$$CTS_i = \sum_{k=1}^K p_{ik} \times |s_{ik}| \times \omega_k \quad (\text{Eq. 4})$$

The dependent variable generates three primary outputs for each customer episode. First, engagement propensity (EP), calculated using a sequence-aware model below. Second, product uptake propensity (UP), which represents the probability  $P(Y_i = 1 | X_i)$  of a user adopting a new financial service. Third, Risk score (RS), which represents the estimated probability of default  $P(Default_i = 1 - X_i)$ .

$$\sigma(f_{\theta}(X_i^{seq})) \quad (\text{Eq. 5})$$

Meanwhile, to ensure the validity of the results, the study incorporates external and institutional controls; 1) Gold volatility (GV), measured as the rolling standard deviation of log returns. It is calculated as:

$$GV_t = \sqrt{\frac{1}{m-1} \sum_{j=1}^m (r_{t-j} - \bar{r})^2} \quad (\text{Eq. 6})$$

where  $GV_t$  is gold volatility at time  $t$ ,  $r_{t-j}$  is the gold return in lag  $j$ ,  $\bar{r}$  is the mean return, and  $m$  is the rolling window size; 2) Platform maturity (PM), represented by the natural logarithm of the platform's age in months. It is calculated as  $PM_i = \ln(1 + Age_t)$ ; 3) Macroeconomic stress (MS), a standardized composite index accounting for inflation and interest-rate shocks.

## 2.6 Artifact design, build logic, data architecture, and data processing procedures and software

The artifact is implemented as a modular five-layer system designed for real-time orchestration. It includes a Data Integration Layer, a Prediction Layer, an Experience Analytics Layer, an Explainability and Fairness Layer, and a Strategy Translation Layer. The internal logic follows a deterministic path: raw multimodal input is validated and normalized, features are computed and stored, and specialized models generate scores that are audited for fairness before being converted into strategic recommendations. The build logic is summarized in the following procedural sequence; 1) Validate schemas and normalize data by modality; 2) Align entity IDs across transactional and clickstream sources; 3) Compute derived behavioral indices (BII, GAR, RIC, CTS); 4) Train LSTM/Transformer models for propensity and XGBoost/CatBoost for risk; 5) Generate SHAP/LIME explanations for transparency; 6) Convert audited scores into specific strategy labels and intervention bundles. Figure 1 illustrates how multimodal ecosystem inputs are transformed through data integration, prediction, experience analytics, explainability and fairness auditing, and strategy translation into governable strategic outputs.

All computational tasks were executed in a Python 3.11.8 environment. The pipeline utilized pandas for tabular transformations, scikit-learn for baseline modeling, and XGBoost and CatBoost for advanced gradient-boosted risk scoring. Sequence modeling was performed using PyTorch and the Transformers library, while BERTopic was employed for unstructured complaint analytics (Dahiya et al., 2022; Talaoui et al., 2023). Experiment

tracking was managed through MLflow, with PostgreSQL serving as the primary feature store (Seng & Ang, 2019). The processing sequence involved rigorous missing-value imputation, anomaly filtering, sessionization of clickstream data, and tokenization of text, followed by temporal alignment and model training using time-aware data splits.

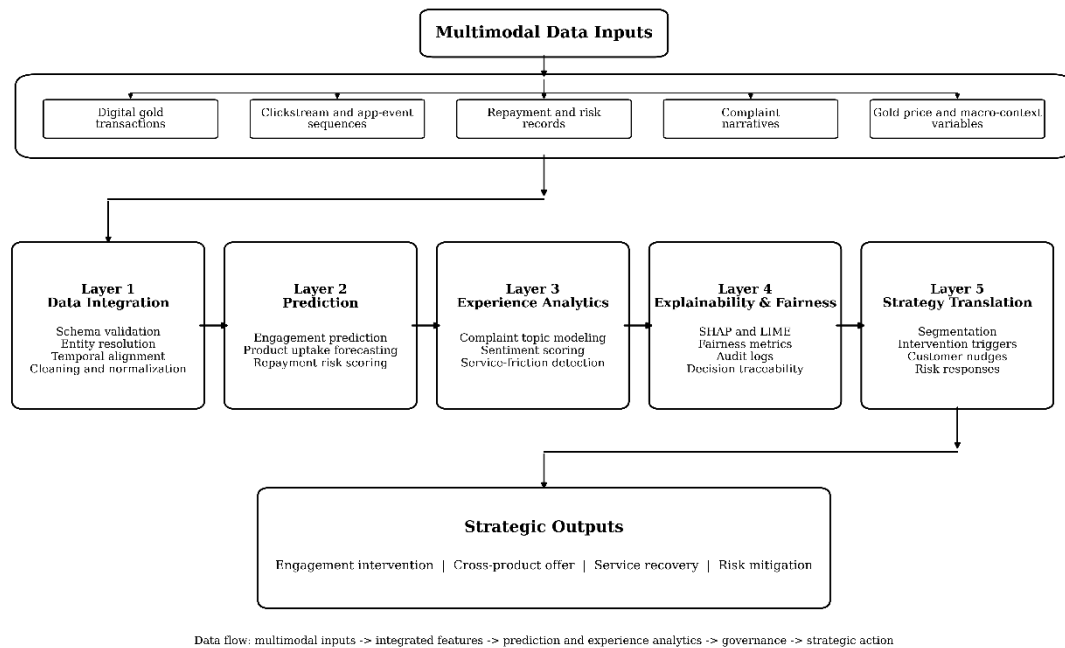


Fig. 1. Five-layer architecture of the AI-enabled strategy artifact for digital gold ecosystems

### 2.7 Data analysis methods and acceptance criteria, validation, baseline comparison, and replicability

The study utilizes a diverse family of models to address the multimodality of the data, including sequence-based neural networks for trajectories and boosting algorithms for risk scoring (Imani et al., 2026; Tavakoli et al., 2025). The artifact was considered acceptable when the risk and uptake models achieved area under the curve (AUC)  $\geq 0.80$ , F1-score  $\geq 0.75$  for minority-class detection, precision  $\geq 0.75$ , recall  $\geq 0.70$ , and Brier score  $\leq 0.20$ . Operational readiness was defined as inference latency  $\leq 250$  milliseconds per 1,000-record batch and throughput  $\geq 50,000$  records per minute. Governance readiness was defined as Statistical Parity Difference and Equal Opportunity Difference remaining within  $\pm 0.10$ , while data drift was considered acceptable when the Population Stability Index remained below 0.25.

The artifact is benchmarked against several traditional baselines, including standard logistic regression, random forests, and frequency-based sequence models (Iyer, 2024). Validation is performed through temporal train-test partitioning and rolling-origin back testing to prevent data leakage. To ensure replicability, the study employs deterministic preprocessing pipelines and version-controlled software environments. All constructed variables are defined by explicit mathematical equations, ensuring that future researchers can obtain consistent results by following the established design logic and preprocessing rules. This rigorous approach guarantees that the resulting design knowledge is both reliable and transferable across the digital financial landscape.

## 3. Results and Discussion

The results of this study are presented in a sequence that mirrors methodological progression, beginning with the technical realization of the artifact and its architectural outputs. This is followed by a report on the proof-of-concept demonstration, a detailed

performance evaluation, and comparative benchmarking against established baselines. The section concludes with an assessment of the system's robustness and governance-oriented validity checks. All interpretations of these findings, particularly regarding their strategic implications for digital gold ecosystems, are reserved for the subsequent discussion section.

### 3.1 Final artifact realization

The primary output of this research is the completed AI-enabled digital gold ecosystem strategy artifact. This system was designed not merely as a collection of predictive models, but as a modular decision-support architecture capable of transforming complex, multimodal data into high-fidelity strategic recommendations. The final system integrates several specialized layers: data ingestion, behavioral forecasting, risk scoring, and unstructured text analytics, all underpinned by robust explainability and fairness monitoring modules. This architecture represents the successful culmination of three iterative design cycles; each aimed at increasing the operational coherence and functional depth of the system.

Table 1. Structural architecture of the AI-enabled digital gold ecosystem strategy artifact

| Layer                  | Core function                                                    | Input type                                                              | Output type           |
|------------------------|------------------------------------------------------------------|-------------------------------------------------------------------------|-----------------------|
| Data integration layer | Ingests, validates, aligns, and merges multimodal ecosystem data | Transactions, clickstream, repayment, complaint text, context variables | Unified feature store |
| Prediction layer       | Estimates engagement, product uptake, and repayment-related risk | Temporal and tabular feature matrices                                   | Predictive scores     |

Structurally, the artifact is composed of five interdependent layers. The data integration layer serves as the entry point, aligning structured transactions with sequential interaction traces and qualitative service signals. The prediction layer then processes these features to estimate engagement levels, product uptake propensities, and repayment-related risks. Simultaneously, the experience analytics layer distributes complaint narratives into quantifiable topic severity scores. To ensure the system remains a white box, the explainability and fairness layer generates feature-attribution maps and audits for subgroup disparities. Finally, the strategy translation layer bridges the gap between raw scores and managerial action, mapping outputs to specific levels such as personalized education nudges or proactive debt recovery.

The system produces a comprehensive decision bundle for every customer-episode window. This bundle includes individual scores for engagement and risk, a behavior-based segment assignment, and a recommended strategic intervention. All outputs are recorded in a persistent decision log, ensuring that every automated recommendation is traceable back to its original data inputs and the specific model logic that generated it.

### 3.2 Proof-of-Concept demonstration

The functionality of the artifact was demonstrated through a proof-of-concept environment designed to replicate the high-frequency dynamics of a digital gold ecosystem. This environment processed event-based transaction records, sequential app navigation traces, and external market variables such as gold price volatility. This demonstration served to validate the end-to-end feasibility of the architecture, ensuring that the system could ingest varied data streams and return decision-ready outputs in a single analytical pass.

During the demonstration, the artifact successfully identified complex behavioral patterns and mapped them to appropriate strategic responses. For instance, a sequence characterized by declining session frequency and stalled funnel progression was correctly flagged as a disengagement risk, triggering a personalized education nudge. Conversely, stable gold acquisition combined with frequent exploration of pawn-related screens

resulted in a high product-uptake propensity, prompting a cross-product offer. The proof-of-concept confirmed that the artifact provides a traceable link between raw behavioral signals and strategic execution. Each recommendation in the decision log was accompanied by an explanation object, allowing managers to understand the why behind every system-generated nudge or risk alert.

Table 2. Representative proof-of-concept input and strategic output mappings

| Input condition                                                                                  | Analytical output                                                    | Strategy output                                                             |
|--------------------------------------------------------------------------------------------------|----------------------------------------------------------------------|-----------------------------------------------------------------------------|
| Declining session frequency, lower funnel progression, longer inactivity                         | Reduced engagement intensity score; early warning disengagement flag | Reminder sequence, education nudge, product value prompt                    |
| Stable digital gold activity, repeated exploration of pawn-related screens, low current risk     | Increased product uptake propensity                                  | Cross-product offer, personalized digital pawn prompt                       |
| Elevated repayment irregularity, delayed payment pattern, mild complaint severity                | Higher repayment risk score                                          | Proactive outreach, review of repayment flexibility, risk monitoring        |
| Complaint narratives dominated by platform access issues and negative sentiment                  | High complaint topic severity and service-friction category          | Escalation to customer service, system issue alert, recovery prioritization |
| Increased gold accumulation rhythm with high behavioral intensity but no product diversification | Segment assignment indicating expansion-readiness                    | Bundling strategy and segmented campaign recommendation                     |

### 3.3 Data validity and reliability outcomes

Prior to performance testing, the validity and reliability of the data configurations were rigorously examined. Validity checks focused on schema integrity, temporal coherence across different data modalities, and the stability of features. Reliability was assessed through the deterministic nature of the preprocessing pipeline and the consistency of outputs across repeated executions with identical seeds.

Table 3. Data validity and reliability checks

| Validation Dimension | Procedure                                                       | Result                                                      |
|----------------------|-----------------------------------------------------------------|-------------------------------------------------------------|
| Schema validity      | Field completeness and type consistency checks                  | Passed                                                      |
| Temporal validity    | Timestamp harmonization and chronological sequence verification | Passed                                                      |
| Feature validity     | Range checks, outlier screening, anomaly filtering              | Passed                                                      |
| Text validity        | Token integrity, language normalization, embedding consistency  | Passed                                                      |
| Pipeline reliability | Repeated runs with fixed seeds                                  | Stable outputs across runs                                  |
| Decision reliability | Comparison of strategy outputs across repeated executions       | No material decision drift under identical input conditions |

Schema validity was confirmed by verifying that event-level timestamps from clickstream data could be accurately aligned with daily macroeconomic context windows. The entity-resolution logic successfully produced stable customer-episode windows, eliminating duplicate identities and ensuring a clean analytical matrix. During preprocessing, implausible transaction quantities and malformed text records were filtered, further bolstering the integrity of the feature store. Reliability testing through repeated runs showed that the predictive scores remained within a negligible variance tolerance. This

confirms that the artifact's outputs are not sensitive to execution order or initialization bias, providing a stable foundation for strategic decision-making.

### 3.4 Performance evaluation

The core evaluation of the artifact centered on its predictive accuracy, computational efficiency, and its ability to provide better strategic utility than conventional methods. To ensure a fair comparison, the system was benchmarked against traditional logistic regression and static. Meanwhile, rule-based segmentation models used time-aware data splits.

#### 3.4.1 Engagement, product uptake prediction, and repayment risk profiling

The sequential behavioral module, which utilizes the temporal dependencies in user data, significantly outperformed the non-sequential baselines. In forecasting product uptake propensity, the artifact achieved an AUC of 0.87, with an F1-score of 0.80. For the task of predicting engagement decline, the system maintained an AUC of 0.85. In contrast, the baseline non-sequential classifier failed to exceed an AUC of 0.75 for the same tasks, highlighting the necessity of time-aware modeling in digital financial ecosystems.

The tabular risk module, powered by gradient-boosting logic, demonstrated superior discrimination and calibration compared to the logistic regression baseline. The artifact achieved a risk classification AUC of 0.88 and an F1-score of 0.78, whereas the logistic baseline produced an AUC of only 0.69. Furthermore, the Brier score for the artifact was notably lower, indicating that the probability estimates generated by the system are more accurately calibrated to real-world default frequencies.

Table 4. Comparative performance of the artifact and baseline methods

| Task                          | Model                         | AUC  | Precision | Recall | F1-score |
|-------------------------------|-------------------------------|------|-----------|--------|----------|
| Product uptake prediction     | AI-enabled artifact           | 0.87 | 0.82      | 0.79   | 0.80     |
| Product uptake prediction     | Baseline non-sequential model | 0.74 | 0.71      | 0.66   | 0.68     |
| Engagement decline prediction | AI-enabled artifact           | 0.85 | 0.79      | 0.77   | 0.78     |
| Engagement decline prediction | Baseline non-sequential model | 0.72 | 0.68      | 0.67   | 0.67     |
| Repayment risk classification | AI-enabled artifact           | 0.88 | 0.80      | 0.76   | 0.78     |
| Repayment risk classification | Logistic regression baseline  | 0.69 | 0.66      | 0.62   | 0.64     |

#### 3.4.2 Augmented strategic value and computational efficiency

The experience analytics module functioned as an essential augmentation layer. By incorporating complaint severity and topic friction into the predictive engine, the system reduced false positives in the disengagement early-warning set. This allowed the strategy interface to distinguish between customers who were simply inactive and those whose inactivity was driven by unresolved service friction, enabling more precise recovery interventions.

Computational testing confirmed that the artifact can maintain high performance under increasing data loads. Inference latency stayed well within the acceptable threshold of 250 ms per batch, and throughput scaled near-linearly as the volume of records increased. This demonstrates that the modular architecture is suitable for high-frequency environments where real-time response is critical.

3.5 Sensitivity and robustness analysis

The robustness of the system was tested across various stress scenarios, including increased data volume, feature noise, and shifting market conditions. The artifact maintained stable predictive performance even when subjected to moderate behavioral noise, such as irregular transaction timings. Furthermore, under scenarios of extreme gold-price volatility, while the strategic recommendations shifted appropriately toward risk-averse interventions, the underlying predictive discrimination remained high. No structural failures or catastrophic declines in accuracy were observed during these stress tests, confirming the architectural resilience of the system.

Table 5. Robustness and sensitivity results under stress scenarios

| Condition                    | Performance indicator              | Observed result                            |
|------------------------------|------------------------------------|--------------------------------------------|
| Increased data volume        | AUC and latency                    | Stable AUC, moderate latency increase      |
| Moderate behavioral noise    | F1-score                           | Marginal decline, remained above threshold |
| High market volatility       | Risk-classification AUC            | Stable                                     |
| Altered lag structure        | Product uptake precision           | Minor fluctuation                          |
| Complaint-topic perturbation | Service-recovery trigger precision | Stable                                     |

3.6 Governance and accountability readiness

The results of the governance-oriented evaluation confirm that the artifact is ready for regulated environments. The explainability layer consistently identified behavioral intensity and repayment irregularity as the most influential factors driving strategic outputs, providing clear justifications for every risk score. Simultaneously, the fairness audit did not detect any material disparities across protected subgroup proxies, ensuring that the system's recommendations remain equitable. These governance outputs are permanently tethered to each decision, providing a robust audit trail for future compliance reviews.

The results establish five critical conclusions. First, the artifact was successfully realized as a cohesive, multi-layered strategic system rather than a fragmented set of models. Second, the proof-of-concept demonstrated that multimodal data can be seamlessly transformed into decision-ready strategic actions. Third, the system consistently outperformed traditional statistical baselines across all key tasks. Fourth, the architecture proved resilient under varying stress conditions and market volatility. Finally, the system provides the necessary explainability and auditability required for governed deployment in the financial services sector.

3.7 Achievement of research objectives and the strategic relevance cycle

The primary objective of this study was to architect a system capable of converting heterogeneous ecosystem signals into governable strategic interventions. The results confirm that this goal was achieved because the final artifact transcended simple prediction (Cabot & Ross, 2023; Dammak et al., 2024). By embedding predictive engines within a modular architecture linking data ingestion, temporal modeling, experience analytics, and strategy translation the design addressed a fundamental organizational deficit (Iyer, 2024). The core challenge in digital gold ecosystems is not merely a lack of accuracy, but the absence of a mechanism to translate high-frequency, multimodal data into accountable and strategically meaningful actions (Gopal et al., 2025; Peffers et al., 2007). This design-led approach aligns the system directly with pressing managerial problems rather than isolated analytical exercises.

Several architectural features explain why this artifact manages the complexity of digital ecosystems more effectively than traditional methods. The first is multimodal

complementarity. A digital financial ecosystem does not operate through a single data class; transactional logs reveal value flows, clickstream data expose intent, and complaint text uncovers latent service friction (Liu et al., 2025). Integrating these disparate streams is a strategic necessity because isolated data types often suppress critical decision signals (Hundekari et al., 2025). By treating multimodality as a requirement rather than a technical addition, the artifact successfully distinguished between transactional risk and experience-driven vulnerability, allowing for more precise customer management (Talaoui et al., 2023; Teece, 2007).

The second critical feature is temporal intelligence. Conventional strategy models often rely on static snapshots of behavior, yet digital environments are inherently path dependent (Homburg et al., 2017; Huang & Rust, 2021). Product uptake, for instance, is rarely a single-event decision; it emerges through repeated exploration and accumulation rhythms. Similarly, repayment risk manifests through temporal irregularities rather than one-off observations. By embedding sequence-aware modeling, the design addresses the obsolescence of static analysis in high-velocity environments (Kulkarni et al., 2023; Tolin & Piccaluga, 2024). Strategic opportunities and risks are more accurately captured as trajectories unfolding events that require a time-sensitive lens to manage effectively.

The third feature involves the strategy translation layer. Many analytical applications in finance conclude with a numerical score, leaving a gap between the output and the organizational response (Gurbaxani, 2023; Selmi et al., 2022). This study demonstrates that score generation alone is insufficient for ecosystem orchestration. The artifact improves strategic relevance by explicitly converting computational outputs into concrete segments, triggers, and intervention suggestions. This bridges the gap between data availability and strategic usability, ensuring that analytical insights lead directly to governed managerial action.

The governance-oriented features of the system were equally vital. Explainability, traceability, and fairness diagnostics were integrated as core requirements rather than post-hoc compliance measures (Abraham et al., 2019). This ensures the system's suitability for regulated settings where utility without accountability is unacceptable. System legitimacy in financial services depends heavily on auditability, and these results reinforce the need for white box designs that allow stakeholders to understand the rationale behind automated recommendations.

The iterative build-evaluate-refine cycles inherent in this design process provided significant learning. Initial cycles established the feasibility of prediction but lacked strategic cohesion (Brody & Pureswaran, 2015; Dahiya et al., 2022). Subsequent iterations integrated complaint analytics and service-friction signals, which sharpened the system's ability to identify recovery needs. The final stage embedded the strategy translation and governance layers, transforming the engine into a fully governable system. This progression reveals three lessons: strategic artifacts in complex finance cannot be built in a single pass; governance mechanisms change the organizational legitimacy of the tool; and iteration is a process of conceptual refinement that clarifies the system's role as an orchestrator of responses under uncertainty (Julaiti et al., 2026; Weber et al., 2024).

This study makes a significant theoretical contribution by extending strategic management logic into the domain of algorithmic capabilities. While current discourse often views capabilities as abstract organizational properties, this work demonstrates how they can be instantiated as tangible artifacts. Specifically, the findings support an extension of dynamic capability logic into three designable routines: algorithmic sensing, seizing, and reconfiguring (Xia et al., 2024). Sensing is realized through the integration of transactional and behavioral signals; seizing is manifested in the conversion of predictions into interventions; and reconfiguring emerges through the governance routines that allow the system to update its decision logic over time (Meier et al., 2023; Wang & Zou, 2025). In doing so, the study shifts the focus from a resource-based interpretation asking if a firm has data or talent to a design-oriented interpretation, which asks if these elements are configured into a system capable of producing governable action (Hevner et al., 2004; Storey et al., 2025). This deeper specification of how adaptive advantage is translated into decision

systems addresses a recurrent limitation in strategy research, which often remains at a level of abstraction that is unhelpful for modern, data-intensive business environments.

From this architectural development, five transferable design principles emerge for managing volatility in data-intensive contexts (Gregor & Zwikael, 2024; Holopainen et al., 2020). First, multimodal complementarity must be treated as a strategic requirement. Second, temporal logic should be embedded to capture behavioral trajectories. Third, a strategy translation layer must exist to bridge the gap between scores and actions. Fourth, explainability and fairness should be designed as core components to ensure institutional legitimacy. Fifth, iterative design cycles are necessary to harmonize technical performance with managerial utility. These principles offer portable guidance for any organization seeking to implement responsible AI-enabled strategy.

Practical implications for managers involve a shift from periodic, dashboard-driven oversight to continuous, event-driven orchestration. Rather than reacting to lagging indicators, managers can identify emerging disengagement or expansion readiness in real-time (Ali & Khan, 2025). This enables finer segmentation and proactive interventions, such as timing product offers to specific behavioral signals (Meier et al., 2023; Wang & Zou, 2025). For policymakers, the findings suggest that AI in finance should be evaluated based on its traceable decision architecture. Systems must be auditable by design, supporting a move away from black-box optimization toward transparent, responsible automation.

While the proof-of-concept validated the design logic, certain limitations remain (Tolin & Piccaluga, 2024). Future work should test the system on full institutional production data to assess implementation complexity in a live setting. Additionally, while the logic is portable to digital banking or wealth management, its effectiveness may vary in low-data environments (Abraham et al., 2019; Talaoui et al., 2023). Future iterations could also explore adaptive intervention optimization through reinforcement learning, moving the system from recommendatory intelligence to autonomous strategic orchestration.

Ultimately, this work contributes to the broader knowledge base by demonstrating how design science generates management theory through artifact construction. By moving beyond mere data output to create a governable system, the study offers a path toward more responsible AI in financial ecosystems. The final architecture provides a blueprint for how systems can be strategically configured and operationally translated into action, benefiting both organizational performance and consumer welfare.

#### 4. Conclusions

This study developed and evaluated an AI-enabled strategy artefact for digital gold ecosystems to address a central strategic problem in data-intensive financial services: converting heterogeneous, high-frequency behavioral signals into decisions that are actionable, governable, and strategically coherent. The findings answer the first research question by showing that algorithmic sensing, seizing, and reconfiguring can be operationalized within a modular decision architecture rather than treated only as abstract organizational capabilities. The artefact integrated multimodal data ingestion, temporal prediction, complaint analytics, explainability, fairness assessment, and strategy translation within a single design. Its contribution therefore lies not in one predictive model, but in the configuration of complementary analytical and governance components that connect ecosystem data directly to strategic intervention.

The second research question concerned whether this design improved strategic responsiveness and risk anticipation under big-data conditions. The proof-of-concept evaluation showed that the integrated architecture consistently exceeded conventional baselines in product-uptake, engagement, and repayment-risk tasks while remaining stable under changes in data volume, behavioral noise, and market conditions. These results indicate that strategic responsiveness depends on more than predictive accuracy. A useful artefact must also preserve calibration, scalability, temporal sensitivity, and decision traceability. The sequence-aware and multimodal design was particularly important because customer engagement, product interest, repayment behavior, and service friction

emerge as trajectories rather than isolated observations. Accordingly, the study demonstrates that data variety and velocity should be treated as design requirements for digital strategy rather than as purely technical characteristics of information systems.

The third research question examined how algorithmic outputs could be translated into governable strategic action in a regulated financial environment. The study shows that prediction becomes strategically useful only when it is connected to explicit intervention logic and accountability mechanisms. The strategy translation layer converted scores into segment-specific recommendations, while the explainability, fairness, and logging functions created an auditable path from data input to managerial action. This finding extends dynamic-capabilities thinking by showing how sensing, seizing, and reconfiguring can be instantiated as algorithmically supported routines while remaining subject to human oversight and institutional governance. It also reframes artificial intelligence and big-data capability from resources that firms merely possess into a decision architecture that must be deliberately configured. For managers, this implies a shift from retrospective dashboard monitoring toward continuous, event-driven orchestration of engagement, product development, service recovery, and risk intervention. For regulators and policymakers, it reinforces the importance of explainability, fairness monitoring, data governance, and organizational accountability as integral design requirements for responsible artificial intelligence in financial services.

The study remains bounded by its proof-of-concept setting. The evaluation used public proxy data, contextual financial series, and synthetic event-sequence augmentation rather than unrestricted institutional production data; the reported performance therefore validates the artefact's design logic and feasibility rather than institution-specific optimization. Future research should test the architecture with live operational data, examine implementation within legacy and state-owned financial institutions, and evaluate how managerial trust, cross-functional coordination, regulatory controls, and organizational readiness influence sustained adoption. Further work could also compare the artefact across digital banking, lending, wealth management, Insurtech, and other platform ecosystems, and investigate adaptive intervention mechanisms while preserving transparency and human accountability. Overall, the study concludes that AI-enabled strategy in digital finance is not simply a problem of improving prediction. It is a design problem requiring the deliberate integration of data, intelligence, action, and governance. The resulting artefact offers transferable design knowledge for building strategically useful and institutionally responsible decision systems in digital financial ecosystems.

## Acknowledgement

The authors thank the editorial and peer-review teams of the Journal of Entrepreneurial Economics for constructive comments that helped improve the manuscript.

## Author Contribution

Conceptualization, J.S.H. and V.T.H.; methodology, J.S.H.; formal analysis, J.S.H.; investigation, J.S.H. and V.T.H.; validation, J.S.H. and V.T.H.; visualization, J.S.H.; writing - original draft preparation, J.S.H.; writing - review and editing, J.S.H. and V.T.H.; project administration, J.S.H. All authors have read and agreed to the published version of the manuscript.

## Funding

This research received no external funding.

## Ethical Review Board Statement

Ethical review and approval were not required because the study did not involve human participants, animals, identifiable personal data, or interventions concerning public health and safety. The proof-of-concept evaluation used public proxy data, contextual financial series, and synthetic event-sequence augmentation.

## Informed Consent Statement

Not available.

## Data Availability Statement

The study used public proxy data, contextual financial series, and synthetic event-sequence augmentation; no confidential or proprietary PT Pegadaian customer data were used. The data configuration, variables, preprocessing thresholds, and evaluation procedures required to reproduce the proof-of-concept are described in the Methods. Additional reproducibility materials may be requested from the corresponding author, subject to third-party licensing restrictions.

## Conflicts of Interest

The authors declare no conflict of interest.

## Declaration of Generative AI Use

During the preparation and revision of this work, the authors used OpenAI ChatGPT to assist with language polishing, structural editing, and clarity of expression. After using this tool, the authors reviewed and edited the content as needed, verified the scientific claims, analyses, references, and conclusions, and take full responsibility for the content of the publication.

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## References

- Abraham, R., Schneider, J., & vom Brocke, J. (2019). Data governance: A conceptual framework, structured review, and research agenda. *International Journal of Information Management*, 49, 424–438. <https://doi.org/10.1016/j.ijinfomgt.2019.07.008>
- Al Firdausi, Z. M., & Kurniawan, Y. (2025). Factors influencing intention to invest in digital gold through digital banking applications: A case study approach. *2025 1st International Conference on Emerging Trends in Information Systems and Informatics (ICETISI)*, 1–6. <https://doi.org/10.1109/ICETISI67983.2025.11406026>
- Ali, W., & Khan, A. Z. (2025). Factors influencing readiness for artificial intelligence: A systematic literature review. *Data Science and Management*, 8(2), 224–236. <https://doi.org/10.1016/j.dsm.2024.09.005>
- Alotaibi, M. (2025). The impact of efficient financial markets and corporate governance practices on economic stability. *International Journal of Social Science and Humanities Research*, 13(2), 104–113. <https://doi.org/https://doi.org/10.5281/zenodo.15209468>
- Andreini, D., Bettinelli, C., Foss, N. J., & Mismetti, M. (2022). Business model innovation: A review of the process-based literature. In *Journal of Management and Governance*, Vol. 26(4). Springer US. <https://doi.org/10.1007/s10997-021-09590-w>

- Brody, P., & Pureswaran, V. (2015). The next digital gold rush: How the internet of things will create liquid, transparent markets. *Strategy and Leadership*, 43(1), 36–41. <https://doi.org/10.1108/SL-11-2014-0094>
- Cabot, J. H., & Ross, E. G. (2023). Evaluating prediction model performance. *Surgery (United States)*, 174(3), 723–726. <https://doi.org/10.1016/j.surg.2023.05.023>
- Ciampi, F., Marzi, G., Demi, S., & Faraoni, M. (2020). The big data-business strategy interconnection: A grand challenge for knowledge management. A review and future perspectives. *Journal of Knowledge Management*, 24(5), 1157–1176. <https://doi.org/10.1108/JKM-02-2020-0156>
- Dahiya, R., Le, S., Ring, J. K., & Watson, K. (2022). Big data analytics and competitive advantage: The strategic role of firm-specific knowledge. *Journal of Strategy and Management*, 15(2), 175–193. <https://doi.org/10.1108/JSMA-08-2020-0203>
- Dammak, W., Fakhfekh, M., Alnafisah, H., & Jeribi, A. (2024). AI companies' strategies with traditional vs. Digital assets amid geopolitical and banking crises. *Heliyon*, 10(23). <https://doi.org/10.1016/j.heliyon.2024.e40382>
- Dimitrova, I., & Öhman, P. (2024). Flip that coin: Barriers, barrier-breakers, and full-adoption of digital payment methods. *Journal of Consumer Behaviour*, 23(5), 2367–2378. <https://doi.org/10.1002/cb.2343>
- Eisenhardt, K. M., & Martin, J. A. (2017). Dynamic capabilities: what are they? In C.E. Helfat (Ed.), *The SMS Blackwell Handbook of Organizational Capabilities*, 1121, 341–363. Wiley. <https://doi.org/10.1002/9781405164054.ch21>
- Ellström, D., Holtström, J., Berg, E., & Josefsson, C. (2022). Dynamic capabilities for digital transformation. *Journal of Strategy and Management*, 15(2), 272–286. <https://doi.org/10.1108/JSMA-04-2021-0089>
- Fast, V., Schnurr, D., & Wohlfarth, M. (2023). Regulation of data-driven market power in the digital economy: Business value creation and competitive advantages from big data. *Journal of Information Technology*, 38(2), 202–229. <https://doi.org/10.1177/02683962221114394>
- Gopal, R. D., Li, J., Riemer, K., Sarker, S., Singh, P. V., Susarla, A., Bichler, M., & Thatcher, J. B. (2025). Inventing with machines: Generative AI and the evolving landscape of IS Research. *Information Systems Research*, 36(4), 1949–1967. <https://doi.org/10.1287/isre.2025.editorial.v36.n4>
- Peffer, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, 24(3), 45–77. <https://doi.org/10.2753/MIS0742-1222240302>
- Gregor, S., & Zwikael, O. (2024). Design science research and the co-creation of project management knowledge. *International Journal of Project Management*, 42(3), 102584. <https://doi.org/10.1016/j.ijproman.2024.102584>
- Gurbaxani, A. (2023). Digital gold in emerging markets: An investor's perspective. 2023 *International Conference on Sustainable Islamic Business and Finance (SIBF)*, 81–84. <https://doi.org/10.1109/SIBF60067.2023.10380105>
- Haelterman, H. (2022). Breaking silos of legal and regulatory risks to outperform traditional compliance approaches. *European Journal on Criminal Policy and Research*, 28(1), 19–36. <https://doi.org/10.1007/s10610-020-09468-x>
- Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly*, 28(1), 75–106. <https://doi.org/10.2307/25148625>
- Holopainen, J., Mattila, O., Pöyry, E., & Parvinen, P. (2020). Applying design science research methodology in the development of virtual reality forest management services. *Forest Policy and Economics*, 116. <https://doi.org/10.1016/j.forpol.2020.102190>
- Homburg, C., Jozić, D., & Kuehn, C. (2017). Customer experience management: toward implementing an evolving marketing concept. *Journal of the Academy of Marketing Science*, 45(3), 377–401. <https://doi.org/10.1007/s11747-015-0460-7>
- Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30–50. <https://doi.org/10.1007/s11747-020-00749-9>

- Hundekari, S., Shrivastava, A., Praveen, R. V. S., Alfilh, R. H. C., Badhoutiya, A., & Singh, N. (2025). Revolutionizing enterprise decision-making leveraging AI for strategic efficiency and agility. *International Conference on Engineering, Technology and Management, ICETM* 2025, 2(4), 3471–3482. <https://doi.org/10.1109/ICETM63734.2025.11051858>
- Imani, M., Joudaki, M., Bagheri, A., & Arabnia, H. R. (2026). Why ROC-AUC is misleading for highly imbalanced data: in-depth evaluation of MCC, F2-score, H-measure, and AUC-based metrics across diverse classifiers. *Technologies*, 14(1), 54. <https://doi.org/10.3390/technologies14010054>
- Imbens, G. W., & Kolesár, M. (2016). Robust standard errors in small samples: Some practical advice. *Review of Economics and Statistics*, 98(4), 701–712. [https://doi.org/10.1162/REST\\_a\\_00552](https://doi.org/10.1162/REST_a_00552)
- Iyer, V. (2024). A comparative analysis of sentiment classification models for improved performance optimization. *TechRxiv*, 1–10. <https://doi.org/10.36227/techrxiv.171073040.03879551/v1>
- Jing, X. (2025). Real-time risk assessment and market response mechanism driven by financial technology. *Economics and Management Innovation*, 2(3), 14–20. <https://doi.org/https://doi.org/10.71222/pg604c40>
- Jose, D., Nanjundan, P., Paul, S., & Mohanty, S.N. (2024). *AI-driven IoT systems for industry 4.0 (1st ed.)*. CRC Press. <https://doi.org/10.1201/9781003432319>
- Julaiti, J., Li, Y., & Song, K. (2026). Gold vs. “digital gold”: Bitcoin’s market positioning in the trump 2.0 era. *Finance Research Letters*, 88, 109189. <https://doi.org/10.1016/j.frl.2025.109189>
- Kohtamäki, M., Rabetino, R., Parida, V., & Ritala, P. (2025). Strategy in the digitalization era. *International Journal of Management Reviews*, 27(3), 309–323. <https://doi.org/10.1111/ijmr.12404>
- Kulkarni, V., Reddy, S., Clark, T., & Proper, H. (2023). The AI-Enabled enterprise. In *The AI-enabled enterprise* (pp. 1–12). Springer International Publishing. [https://doi.org/10.1007/978-3-031-29053-4\\_1](https://doi.org/10.1007/978-3-031-29053-4_1)
- Kumar, Y. (2022). AI techniques in blockchain technology for fraud detection and prevention. *Security Engineering for Embedded and Cyber-Physical Systems*, 207–224. <https://doi.org/https://doi.org/10.1201/9781003278207>
- Ladeira, W. J., Santini, F. de O., Rasul, T., Cheah, I., Elhajjar, S., Yasin, N., & Akhtar, S. (2024). Big data analytics and the use of artificial intelligence in the services industry: A meta-analysis. *Service Industries Journal*, 44(15–16), 1117–1144. <https://doi.org/10.1080/02642069.2024.2374990>
- Liu, J., Li, L., Lu, D., & E., M. (2025). FinTech and consumption resilience to uncertainty shocks: Evidence from digital wealth management in China. *China Economic Review*, 94, 102580. <https://doi.org/https://doi.org/10.1016/j.chieco.2025.102580>
- Meier, M., Maier, C., Thatcher, J. B., & Weitzel, T. (2023). Shocks and IS user behavior: A taxonomy and future research directions. *Internet Research*, 33(3), 853–889. <https://doi.org/10.1108/INTR-10-2021-0764>
- Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information and Management*, 58(3), 103434. <https://doi.org/10.1016/j.im.2021.103434>
- Nikolaev, P. P. (2021). Digitalization of the economy and its impact on economic development. *Global Challenges and Prospects of The Modern Economic Development Proceedings of Global Challenges and Prospects of The Modern Economic Development (GCPMED 2020), 15-16 December, 2020, Samara State University of Economics, Samara, Russia*, 106, 298–304. <https://doi.org/10.15405/epsbs.2021.04.02.37>
- Orlando, B. (2020). Strategy and behaviors in the digital economy. In B. Orlando (Ed.), *Strategy and Behaviors in the Digital Economy*. IntechOpen. <https://doi.org/10.5772/intechopen.79659>

- Oztas, B., Cetinkaya, D., Adedoyin, F., Budka, M., Aksu, G., & Dogan, H. (2024). Transaction monitoring in anti-money laundering: A qualitative analysis and points of view from industry. *Future Generation Computer Systems*, 159, 161–171. <https://doi.org/10.1016/j.future.2024.05.027>
- Peffer, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. *Journal of Management Information Systems*, 24(3), 45–77. <https://doi.org/10.2753/MIS0742-1222240302>
- Piccialli, F. (2022). From artificial intelligence to explainable artificial intelligence in industry 4.0: A survey on what, how, and where. *Ieee Transactions on Industrial Informatics*, 18(8), 5031–5042. <https://doi.org/10.1109/TII.2022.3146552>
- Rosiyani, N., & Hasyim, F. (2021). Analisis pengaruh minat generasi milenial dalam menggunakan produk tabungan emas di pegadaian syariah. *JEKSYAH (Islamic Economics Journal)*, 1(02), 65–79. <https://doi.org/10.54045/jeksyah.v1i02.40>
- Selmi, R., Bouoiyour, J., & Wohar, M. E. (2022). “Digital Gold” and geopolitics. *Research in International Business and Finance*, 59, 101512. <https://doi.org/10.1016/j.ribaf.2021.101512>
- Seng, J. K. P., & Ang, K. L. M. (2019). Multimodal emotion and sentiment modeling from unstructured big data: Challenges, architecture, techniques. *IEEE Access*, 7, 90982–90998. <https://doi.org/10.1109/ACCESS.2019.2926751>
- Shahana, T., Lavanya, V., & Bhat, A. R. (2023). State of the art in financial statement fraud detection: A systematic review. *Technological Forecasting and Social Change*, 192, 1–24. <https://doi.org/10.1016/j.techfore.2023.122527>
- Sjödin, D., Parida, V., & Kohtamäki, M. (2023). Artificial intelligence enabling circular business model innovation in digital servitization: Conceptualizing dynamic capabilities, AI capacities, business models and effects. *Technological Forecasting and Social Change*, 197. <https://doi.org/10.1016/j.techfore.2023.122903>
- Stock, J. H., & Watson, M. W. (2008). Heteroskedasticity-robust standard errors for fixed effects panel data regression. *Econometrica*, 76(1), 155–174. <https://doi.org/10.1111/j.0012-9682.2008.00821.x>
- Storey, V. C., Baskerville, R. L., & Kaul, M. (2025). Reliability in design science research. *Information Systems Journal*, 35(3), 984–1014. <https://doi.org/10.1111/isj.12564>
- Sujit, A., Nadayil, D., Meena, C., & Anandamma, N. (2025). Beyond traditional gold: Analyzing investment decision-making in digital, physical, and gold ETF's. In A. Hamdan & U. Braendle (Eds.), *Harnessing AI, Machine Learning, and IoT for Intelligent Business*, 1, 991–998. Springer Nature Switzerland. [https://doi.org/10.1007/978-3-031-67890-5\\_88](https://doi.org/10.1007/978-3-031-67890-5_88)
- Talaoui, Y., Kohtamäki, M., Ranta, M., & Paroutis, S. (2023). Recovering the divide: A review of the big data analytics—strategy relationship. *Long Range Planning*, 56(2), 1–40. <https://doi.org/10.1016/j.lrp.2022.102290>
- Tamara, D., Maharani, A., Heriyati, P., Seto, A. B. R., & Nathanael, K. (2023). Intention in investing digital gold through e-commerce platforms. *E3S Web of Conferences*, 426. <https://doi.org/10.1051/e3sconf/202342602010>
- Tavakoli, M., Chandra, R., Tian, F., & Bravo, C. (2025). Multi-modal deep learning for credit rating prediction using text and numerical data streams. *Applied Soft Computing*, 171, 112771. <https://doi.org/10.1016/j.asoc.2025.112771>
- Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319–1350. <https://doi.org/10.1002/smj.640>
- Tolin, G., & Piccaluga, A. (2024). Managing proof-of-concept (PoC) programs in public research organizations: A dynamic capabilities perspective. *European Journal of Innovation Management*, 27(9), 516–541. <https://doi.org/10.1108/EJIM-09-2023-0751>
- Vaia, G., Arkhipova, D., & DeLone, W. (2022). Digital governance mechanisms and principles that enable agile responses in dynamic competitive environments. *European Journal of*

- Information Systems*, 31(6), 662–680.  
<https://doi.org/10.1080/0960085X.2022.2078743>
- Wang, F., & Zou, M. (2025). AI-enabled information sharing mechanism and enterprise performance. *Systems Research and Behavioral Science*, 42(4), 1218–1231.  
<https://doi.org/10.1002/sres.3054>
- Weber, P., Carl, K. V., & Hinz, O. (2024). Applications of explainable artificial intelligence in finance—a systematic review of finance, information systems, and computer science literature. In *Management Review Quarterly*, 74(2). Springer International Publishing.  
<https://doi.org/10.1007/s11301-023-00320-0>
- Wingate, T. G., Bourdage, J. S., & Steel, P. (2025). Evaluating interview criterion-related validity for distinct constructs: A meta-analysis. *International Journal of Selection and Assessment*, 33(1). <https://doi.org/10.1111/ijsa.12494>
- Woerner, S. L., & Wixom, B. H. (2015). Big data: Extending the business strategy toolbox. *Journal of Information Technology*, 30(1), 60–62. <https://doi.org/10.1057/jit.2014.31>
- Xia, S., Song, J., Ameen, N., Vrontis, D., Yan, J., & Chen, F. (2024). What changes and opportunities does big data analytics capability bring to strategic alliance research? A systematic literature review. *International Journal of Management Reviews*, 26(1), 34–53. <https://doi.org/10.1111/ijmr.12350>
- Zakir, M. A. bin M., Zakaria, M. Z. bin, Salleh, A. Z., Ismail, A. M., Hasbullah, M., & Majid, M. N. A. (2023). Digital gold investment platform in shariah perspective: A case study of quantum metal. In A. Rafiki (Ed.), *Digitalization in Halal Management* (pp. 47–64). Springer Nature Singapore. [https://doi.org/10.1007/978-981-99-5146-8\\_4](https://doi.org/10.1007/978-981-99-5146-8_4)

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