TEPIAN Vol. 7 No. 2 (June 2026) 143-151 p-ISSN 2721-5350 e-ISSN 2721-5369
https://doi.org/10.51967/tepian.v7i2.3657

Multi-stream Revenue Model for AI-based Fintech Lending using Enterprise Architecture Framework

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Submitted: 2026-01-13; Accepted: 2026-05-11; Published: 2026-06-01

***Abstract*—** The contemporary Peer-to-Peer (P2P) lending industry is currently facing existential sustainability challenges, primarily driven by intense market saturation and the escalating risk of Non-Performing Loans (NPL). Conventional business models, which rely heavily on interest-based income, are proving increasingly fragile in this volatile financial landscape. Addressing these critical vulnerabilities, this study proposes a comprehensive Enterprise Architecture (EA) framework to transform Fintech platforms from traditional loan intermediaries into intelligent, data-driven financial orchestrators effectively integrated within a Smart Urban Ecosystem. Methodologically, the research adopts a systematic qualitative Design Science Research (DSR) approach, synthesizing the Business Model Canvas for strategic alignment and ArchiMate 3.1 standards for technical structural modeling. The study critiques the limitations of existing monolithic systems and introduces a novel multi-stream revenue model designed to diversify income sources. This model comprises three core pillars: AI-based Credit Scoring as a Service (CSaaS) to foster cross-platform interoperability and trust, Credit Behavior Analytics, which monetizes previously underutilized "dark data" for deeper risk insights, and Embedded Credit Scoring tailored for real-time, high-frequency transactional environments. Technically, the proposed architecture strategically decouples high-load AI computation from low-latency decisioning processes using a microservices approach, thereby resolving scalability bottlenecks often found in legacy systems. The findings demonstrate that transitioning to this modular "Fintech-as-a-Service" paradigm significantly mitigates financial risk by shifting reliance from uncertain loan interest to stable, fee-based revenue streams. This research provides a strategic blueprint for Fintech stakeholders, offering a pathway to long-term viability and competitive advantage in the emerging data-driven digital economy.

***Keywords*—**Enterprise Architecture, Fintech Orchestration, Smart Urban Ecosystem, AI Credit Scoring, Sustainable Business Model.

I. Introduction

The rapid and disruptive evolution of financial technology (Fintech) has fundamentally reshaped the global economic landscape, establishing Peer-to-Peer (P2P) lending not merely as an alternative funding source, but as a critical driver of digital financial inclusion. In the last decade, the symbiosis between digital platforms and financial services has created new ecosystems that aggressively challenge traditional banking models by offering superior agility and accessibility (Murati & Skau, 2024). According to recent global financial data, the proliferation of digital payments and lending platforms has been instrumental in supporting economic resilience during global crises, providing liquidity to underserved sectors where conventional banks are often absent (Demirg et al., 2021). Despite this robust trajectory, the conventional P2P lending industry is currently approaching a critical saturation point characterized by fierce competition, customer churn, and shrinking profit margins.

A significant and escalating vulnerability in this sector is the reliance on a monolithic, interest-based revenue model. This traditional approach is increasingly susceptible to market volatility and the rising risk of Non-Performing Loans (NPL), particularly in developing economies where credit histories are often fragmented. The integration of Artificial Intelligence (AI) has become a critical necessity in modern Fintech platforms. Recent advancements show that AI fundamentally transforms credit accessibility and significantly enhances the accuracy of risk assessment processes to mitigate the escalating risk of Non-Performing Loans (Adewale, 2025). Regulatory bodies have responded to these systemic risks with tighter frameworks; for instance, recent regulations emphasize that platforms failing to mitigate credit risks or maintain capital adequacy face stringent compliance penalties, threatening their operational continuity (Otoritas Jasa Keuangan, 2022). Extensive literature on banking risk management suggests that traditional statistical methods are no longer sufficient to handle the complexity and volume of modern borrower profiles without the aid of advanced machine learning and predictive analytics (Arifah & Nihaya, 2023). The inability to accurately predict default probability in real-time has become a fatal bottleneck for many first-generation lending platforms.

The global urbanization paradigm is shifting towards the 'Smart Urban Ecosystem,' where cross-sector interoperability becomes mandatory rather than optional. This transition presents a strategic momentum for Fintech companies to pivot from being mere intermediaries to becoming financial orchestrators that underpin vital urban sectors, particularly Property Technology (PropTech). Recent systematic reviews indicate that the digitalization of real estate markets requires seamless financial integration to enhance asset efficiency and user experience (Tagliaro et al., 2024). A major technological gap remains: the massive volume of resident behavioral data—often termed "dark data"—is frequently generated but left unexploited. Recent studies argue that if this alternative data (e.g., utility payments, rental history, e-commerce usage) is processed through AI-driven architecture, it can yield credit risk insights that are significantly more precise than traditional metrics, especially for unbanked populations (Kumar & Sharma, 2023).

Addressing this integration complexity requires a structured, rigorous, and scalable approach, namely Enterprise Architecture (EA). While foundational theories have long established EA as a strategic instrument for aligning IT with business execution (Alghamdi, 2024), more recent technical scholarship emphasizes the urgent need for modular microservices architectures to ensure scalability and agility in high-frequency Fintech operations (Wu, 2024). To ensure the seamless integration and scalability of these multi-stream revenue models, the development of a robust Enterprise Architecture (EA) is essential. Implementing a structured EA framework within digital banking and Fintech environments effectively aligns strategic business objectives with the underlying IT capabilities (Sentosa, Indrajit, & Dazki, 2024). Legacy monolithic systems are ill-equipped to handle the diverse API demands of a smart city ecosystem. To ensure sustainable ecosystem collaboration, the alignment of business models is a prerequisite. By synthesizing the ArchiMate modeling standards with the platform revolution strategy (The Open Group, 2019; Yeh et al., 2024), Fintech platforms can design diversified, fee-based revenue streams—such as Credit Scoring as a Service (CSaaS) and behavioral analytics. This shift allows firms to innovate their value proposition, reducing dependency on high-risk interest income in favor of recurring service-based revenues (Budiman & Fithri, 2025).

Responding to these multifaceted challenges, this study aims to design a comprehensive Enterprise Architecture that transforms a Fintech Lending platform into a provider of intelligent financial infrastructure within a Smart City ecosystem. The research adopts a Design Science Research (DSR) approach to ensure both academic rigor and practical relevance. The primary contributions of this research are twofold: the development of a business architecture model that diversifies revenue through data monetization and B2B API services and the formulation of a technology architecture that ensures high scalability and interoperability in accordance with modern digital ecosystem standards.

Despite the rapid advancement of Fintech architectures and AI-driven credit systems, a critical research gap remains in the integration of revenue diversification strategies within Enterprise Architecture frameworks for P2P lending platforms. Most existing studies primarily focus on improving credit scoring accuracy or enhancing user acquisition, while overlooking the structural dependency on interest-based revenue models that expose platforms to systemic financial risks.

Prior research on Fintech ecosystem orchestration has largely emphasized technological scalability without adequately addressing sustainable monetization mechanisms derived from data assets. In many real-world platforms, large volumes of behavioral and transactional data are generated continuously but remain underutilized due to the absence of a structured analytics architecture. This phenomenon, often referred to as “dark data,” represents a latent strategic asset that can be transformed into new revenue streams if properly governed through an Enterprise Architecture approach.

The existing literature rarely bridges the conceptual alignment between Smart City ecosystems and Fintech platform infrastructure. While Smart Urban Ecosystems demand interoperable financial services, most P2P lending platforms still operate as isolated financial intermediaries rather than intelligent infrastructure providers. This fragmentation creates inefficiencies in cross-sector data exchange, particularly in PropTech, digital commerce, and urban service integration.

This research introduces a novel contribution by synthesizing Enterprise Architecture, AI-driven analytics, and multi-stream revenue design into a unified Fintech-as-a-Service model. Unlike conventional studies that focus solely on loan processing optimization, this study proposes a strategic transformation toward an intelligent financial orchestration platform capable of monetizing data, APIs, and embedded financial services within a broader digital ecosystem.

II. METHODOLOGY

To design a financial architecture that is not only technically robust but also strategically aligned with the Smart City ecosystem, this study adopts a systematic qualitative approach grounded in Design Science Research (Febriyanto et al., 2024), which remains a foundational framework for developing and evaluating innovative IT artifacts in modern enterprise ecosystems (Elwahab et al., 2023). The methodology is structured into two mutually reinforcing phases: the formulation of a theoretical framework and a comprehensive data collection strategy.

A. Theoretical Framework

The primary challenge currently facing the Fintech industry is the need to balance rapid user growth with risk management resilience. To unravel this complexity, this study employs a multi-dimensional framework comprising business strategy, architectural design, and technological foundation:

1. Business Model Canvas (BMC) for Ecosystem Strategy: Before proceeding to technical design, the crucial first step is to redefine the business strategy. This study employs the Business Model Canvas (BMC) (Budiman & Fithri, 2025) to map the transformation from a linear lending model to an ecosystem platform. This shift aligns with the "Platform Revolution" theory, which emphasizes value creation through external interactions rather than internal production (Yeh et al., 2024). The proposed business model canvas can be seen in Figure 1.

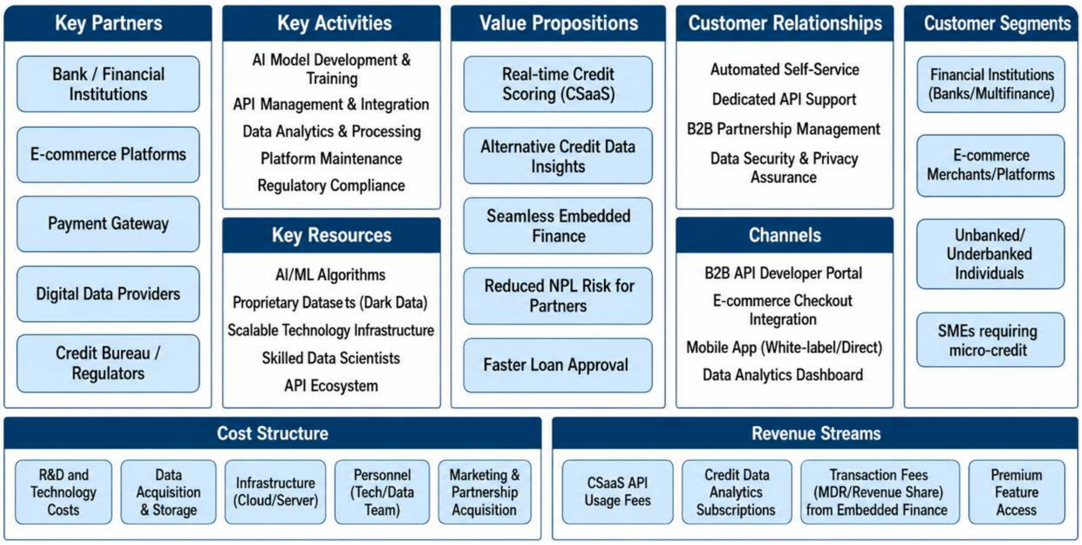

Figure 1. Proposed Business Model Canvas for Fintech Ecosystem Orchestration

2. Layered Architecture Modeling with ArchiMate 3.1: To translate this business strategy into an executable technology blueprint, the ArchiMate 3.1 modeling language is employed. This standard was selected for its ability to precisely visualize the interrelationships between layers (Wu, 2024). The modeling is conducted across three core layers:
   a. Business Layer: Maps the complex interactions between actors (such as Banks, Property Developers, and Platforms) and the data orchestration business processes.
   b. Application Layer: Defines software components, including microservices for BNPL processing and the B2B interface (API Gateway) for scoring services (CSaaS).
   c. Technology Layer: Specifies the underlying infrastructure specifications required to support high availability, such as the use of cloud computing nodes and in-memory caching mechanisms.
3. Technological Foundation: The core enabler is Artificial Intelligence (AI). Unlike traditional scoring that excludes the unbanked, AI allows for the analysis of alternative data to predict creditworthiness with high accuracy (Kumar & Sharma, 2023). The architecture is designed to comply with ISO 37106 standards for smart city operating models, ensuring future interoperability (International Organization for Standardization, 2018).

B. Data Collection

The validity of the architectural design proposed in this study is grounded in a systematic and multi-source data collection process. To ensure both theoretical rigor and practical relevance, data were gathered using two complementary approaches :

1. Literature Study and Regulatory Review : An in-depth review of recent academic literature was conducted using key themes such as "Smart City Orchestration," "PropTech Business Models," and "Data-Driven Fintech." This review aimed to identify existing research gaps and emerging opportunities related to the integration of Fintech within smart urban ecosystems (Tagliaro et al., 2024). In parallel, relevant global technical and regulatory standards were examined, including Context Information Management for smart city interfaces (ETSI, 2018) and ISO 37106 for sustainable operating models (International Organization for Standardization, 2018). Local regulatory compliance was ensured by analyzing the latest provisions on information technology-based joint funding services (Otoritas Jasa Keuangan, 2022).
2. Empirical data were obtained through direct observation of operational workflows in existing P2P lending platforms. The observation focused on critical stages of the credit assessment process, particularly the dependence on manual verification and the limited utilization of alternative data sources (Arifah & Nihaya, 2023). Insights from these observations were synthesized to perform an Architecture Gap Analysis, comparing the current "As-Is" condition—

characterized by fragmented processes and high operational risk—with the proposed "To-Be" condition, which emphasizes orchestration and automation. This analysis is crucial for ensuring the strategic alignment of the proposed architecture (Alghamdi, 2024). The research methodology flowchart can be seen in Figure 2.

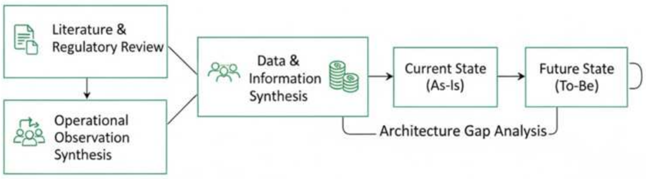

Figure 2. Research Methodology Flowchart: From Data Collection to Architecture Gap Analysis

C. Design Science Research Justification

The adoption of Design Science Research (DSR) in this study is particularly relevant due to the problem-solving nature of Fintech architectural design. Unlike purely observational research, DSR enables the development of an innovative artifact—in this case, a multi-stream revenue Enterprise Architecture—that addresses real-world industry challenges such as Non-Performing Loan (NPL) risk, data underutilization, and scalability constraints.

The DSR process in this research follows three iterative cycles: relevance cycle, rigor cycle, and design cycle. The relevance cycle ensures that the proposed architecture aligns with practical industry needs observed in P2P lending operations. The rigor cycle integrates established theoretical foundations including Enterprise Architecture principles, Business Model Canvas, and AI-driven credit analytics. Meanwhile, the design cycle focuses on constructing and refining the architectural artifact through gap analysis and layered modeling using ArchiMate 3.1.

This methodological approach ensures that the proposed solution is not only theoretically grounded but also practically implementable in real Fintech environments. By combining qualitative observation with architectural modelling, the research maintains methodological rigor while delivering a prescriptive framework suitable for digital financial ecosystems.

III. Results and Discussion

A. Operational Analysis and Requirements

Based on the data collection phase (observation and documentation review), specific inefficiencies were identified in the legacy lending process. The analysis, summarized in Table I, highlights the critical "Pain Points" that the new Enterprise Architecture aims to resolve.

Table 1. Operational Gap Analysis (Observation Findings)

Operational Domain	Existing Process Issues	Identified Pain Points	Architectural Requirement (Solution)
Credit Assessment	Manual verification of physical documents by analysts.	High Latency: Approval takes 2-3 days. Human error risk is high.	Automated AI Scoring (U2) integrated with external data (S1-S4) for instant approval.
Revenue Model	90% revenue dependency on loan interest (spread).	High Risk: Vulnerability to NPL. Revenue stops if borrowers default.	Diversification: Create fee-based streams (API & Analytics) independent of loan repayment.
Data Utilization	Transaction logs are archived in "Cold Storage" and unused.	Wasted Asset: Valuable behavioral data generates no value ("Dark Data").	Analytics Engine (U4): Monetizing insights for institutional clients (C2).
User Experience	Borrowers must switch apps to apply for loans.	High Drop-off: Complex user journey reduces conversion.	Embedded Architecture (R3): Integrate scoring directly into E-commerce (S12).

B. Strategic Ecosystem and Actor Mapping

To implement the solutions identified above, the Enterprise Architecture is redesigned as an open ecosystem. Utilizing ArchiMate modelling, the system maps interactions between Customers (C), External Suppliers (S), and Internal Resources (U). This high-level application architecture can be seen in Figure 3.

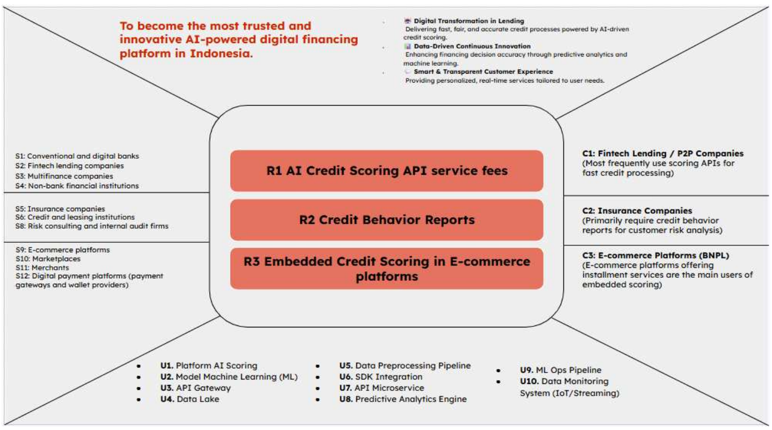

Figure 3. High-Level Application Architecture showing the ecosystem of Revenue Streams

C. Detailed Architectural Design

The following sections detail the ArchiMate modelling for each revenue stream, explaining the data flow between the mapped entities.

1. Revenue Stream 1

AI Credit Scoring as a Service (CSaaS) This stream monetizes the scoring technology via a "Pay-per-Hit" model for B2B Partners. The CSaaS model utilizes artificial intelligence to process unstructured and behavioral alternative data, providing a more holistic and adaptive view of borrower risk compared to traditional models (Junaedi et al., 2024). By adopting AI-driven analytics, Fintech companies can transition from conventional credit scoring to proactive financial risk management. This intelligent approach is vital for mitigating defaults and ensuring the long-term operational sustainability of the lending platform (Nuraziza & Sudirman, 2024). The layered architecture for this revenue stream can be seen in Figure 4.

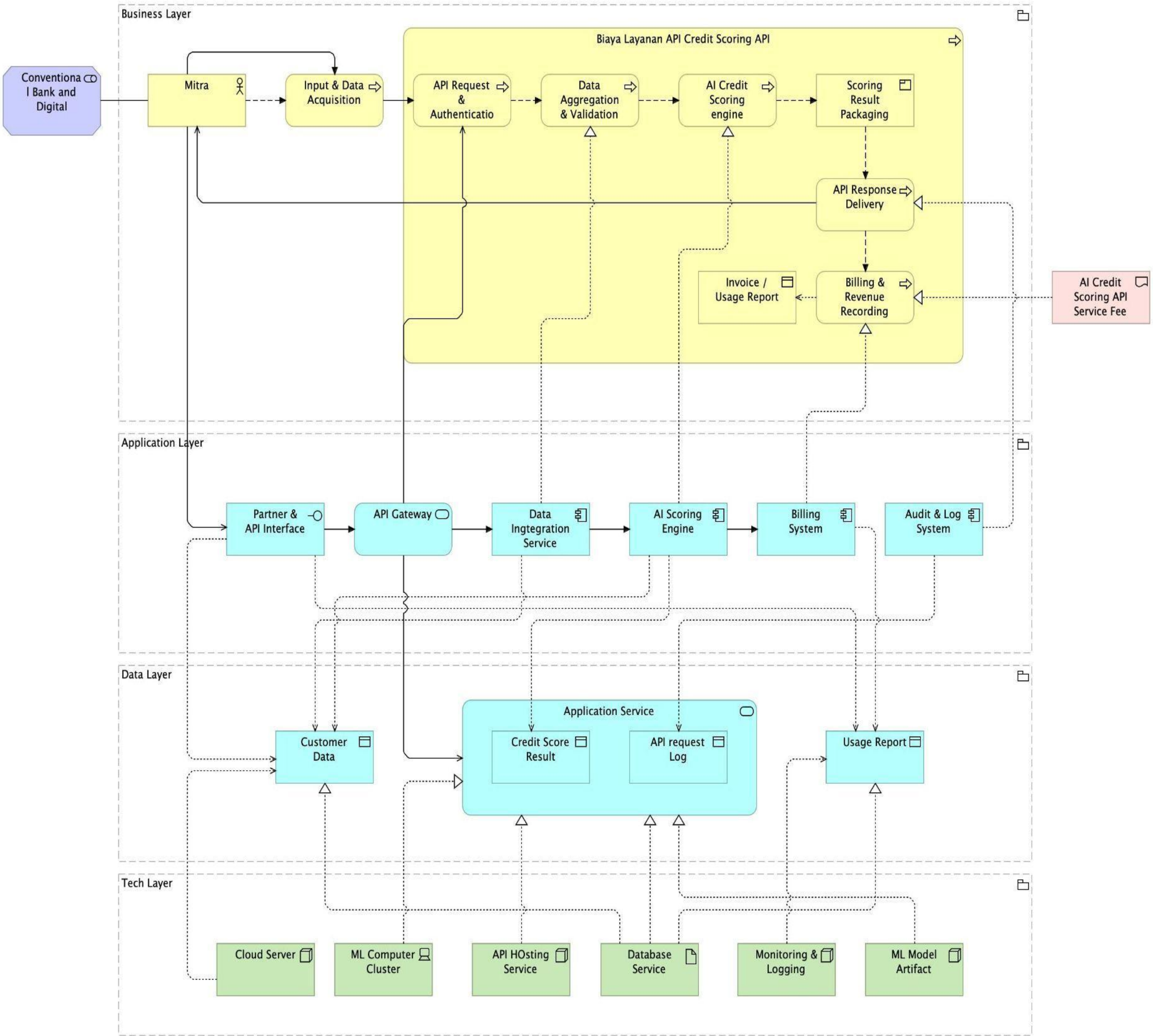

Figure 4. Layered Architecture for Revenue Stream 1 (CSaaS)

a. Technical Workflow
The process begins when C1 (Fintech Lending) transmits a borrower's data payload via HTTPS to U3 (API Gateway), which intercepts the request for token validation before routing the authenticated traffic to U1 (Platform AI Scoring). Because U1 requires structured input, it activates the U5 (Data Preprocessing) pipeline, allowing U2 (Model Machine Learning) to subsequently generate a prediction score based on the cleaned data. This prediction is then validated by cross-referencing it with information from external Financial Partners (S1-S4), all while U4 (Data Lake) systematically logs every step of the entire workflow to ensure future auditability

b. Revenue Trigger
Monetization: The billing module connected to U3 records a billable event. Consequently, C1 incurs a fixed fee for every successful API response.

2. Revenue Stream 2

Credit Behavior Analytics Report This stream monetizes data assets via a "Subscription" model for Institutional Clients. The layered architecture for Revenue Stream 2 can be seen in Figure 5.

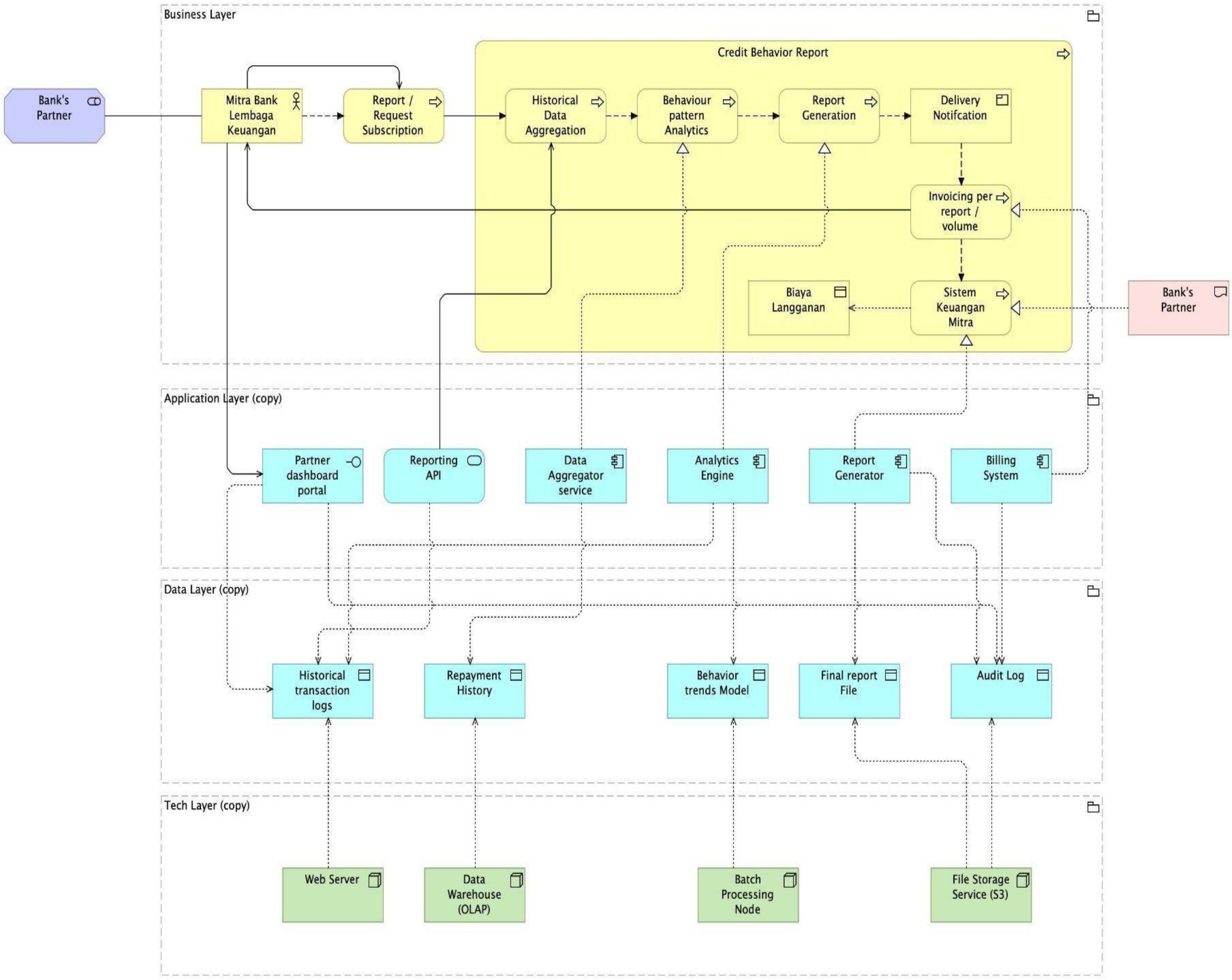

Figure 5. Layered Architecture for Revenue Stream 2 (Analytics)

a. Technical Workflow
Operating on a scheduled batch basis, the data pipeline begins when U8 (Predictive Analytics Engine) extracts historical datasets from U4 (Data Lake). To provide the necessary context for institutional reporting, U8 enriches this internal data by analyzing long-term trends and potentially integrating risk perspectives from Risk Consultants (S8) or Insurance Partners (S5). Once the data is enriched, the system compiles these insights into a comprehensive risk report, while U9 (ML Ops Pipeline) operates continuously within this layer to ensure the underlying analytics models remain updated with the latest market behavior.

b. Revenue Trigger
Monetization: Revenue recognition occurs when C2 pays the subscription fee to access these periodic reports generated by U8.

3. Revenue Stream 3

Embedded Credit Scoring (BNPL) This stream monetizes traffic via a "Transaction Fee (MDR)" model embedded in E-commerce. This stream monetizes traffic via a 'Transaction Fee (MDR)' model embedded in E-commerce. The integration of BNPL within e-commerce checkout processes has surged significantly, migrating consumer credit volumes toward embedded lending channels (Murati & Skau, 2024). The layered architecture for Revenue Stream 3 can be seen in Figure 6.

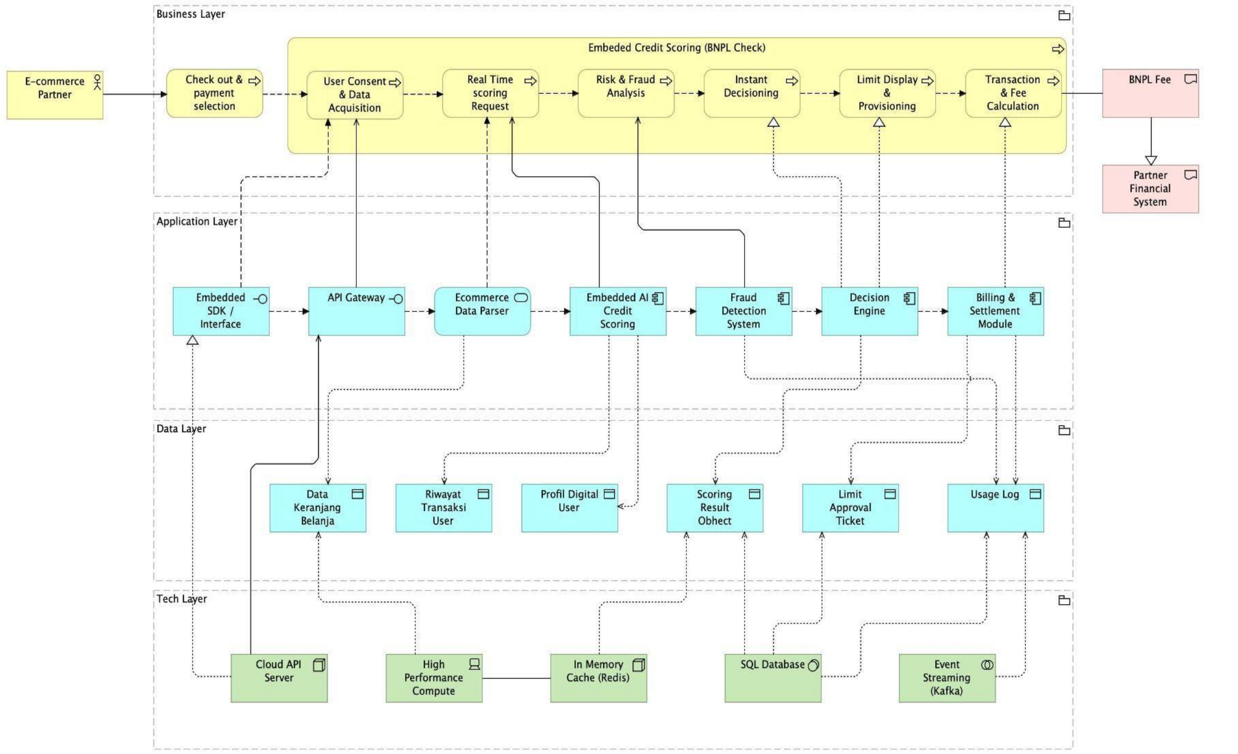

Figure 6. Layered Architecture for Revenue Stream 3 (Embedded BNPL)

a. Technical Workflow
To facilitate seamless usage, the platform utilizes U6 (SDK Integration) directly within its checkout page. Because speed is paramount during these real-time checks, S12 (Payment/Wallet) triggers a request the moment a user initiates a payment, with U7 (API Microservice) specifically stepping in to handle the high-concurrency traffic. U7 then instantly queries U1 (Platform AI) for a decision, relying crucially on contextual data gathered from the Digital Ecosystem (S9-S11) to validate the transaction's legitimacy. Throughout this process, to prevent cart abandonment, U10 (Data Monitoring) actively tracks system latency, ensuring that the entire decision loop is completed in under 500ms.

b. Revenue Trigger
Monetization: The system applies a Merchant Discount Rate (MDR) to the total transaction value processed by S12, which is then shared between the platform and C3.

D. Discussion

The detailed architecture proves that revenue diversification is technically feasible through component reuse:

1. Latency Management: The architecture strategically separates *Synchronous Processing* (Stream 1) for high precision and *Microservice Processing* (Stream 3) for speed. This distinction prevents heavy B2B requests from disrupting B2C checkout flows.
2. Data Monetization: The design effectively converts "Cold Data" stored in the Data Lake (U4) into a profit center (Stream 2), demonstrating that historical logs possess significant value when processed correctly.
3. Scalability: By decoupling components such as the API Gateway (U3) and AI Platform (U1), the system enables targeted resource scaling where traffic is highest, avoiding the need to upgrade the entire monolithic system.

E. Economic Feasibility and Sustainability Analysis

From an economic perspective, the proposed multi-stream revenue architecture significantly enhances the financial sustainability of Fintech lending platforms. Traditional interest-based models are inherently volatile due to their direct exposure to borrower default rates and macroeconomic fluctuations. By contrast, the introduction of API-based scoring services, subscription analytics, and embedded transaction fees creates diversified and recurring revenue channels that are less sensitive to credit risk volatility.

The CSaaS (Credit Scoring as a Service) model introduces a scalable B2B monetization mechanism where revenue is generated per API call, independent of loan disbursement success. This decoupling of revenue from lending performance reduces financial dependency on borrower repayment behavior. Similarly, the Credit Behavior Analytics stream transforms historical operational logs into subscription-based intelligence products, thereby converting previously idle data storage into a strategic profit center.

The Embedded Credit Scoring model (BNPL integration) aligns with high-frequency digital commerce environments, enabling revenue generation through Merchant Discount Rate (MDR) sharing. This model not only increases transaction volume but also enhances user retention by embedding financial services directly within digital platforms. As a result, customer acquisition costs can be reduced while lifetime value (LTV) increases due to ecosystem lock-in effects.

From a long-term sustainability standpoint, the architecture supports a transition from a high-risk financial intermediary model to a platform-based service model. This shift is aligned with platform economy theory, where value creation is driven by ecosystem interactions rather than solely by core financial products. The platform gains resilience against market saturation and regulatory pressure, as its revenue streams are distributed across multiple service layers instead of relying on a single income source.

F. Managerial and Practical Implications

The architectural model developed in this study delivers highly practical value for the day-to-day operations of fintech lending platforms. From a strategic management perspective, the proposed framework acts as a vital blueprint to help companies navigate the shift from rigid, monolithic lending operations toward a much more flexible, modular Fintech-as-a-Service approach. By doing so, platforms can scale their core services effectively and tap into broader digital ecosystems without losing their operational agility.

Beyond just business operations, this transition directly addresses the increasingly strict compliance demands in the financial sector. The design introduces a centralized Data Lake combined with active monitoring modules, making real-time risk surveillance, compliance audits, and regulatory reporting much more straightforward. Instead of relying on opaque or "black-box" AI models, regulators are provided with transparent, auditable data pipelines that significantly enhance overall risk governance.

The proposed open API structure enables smoother collaboration with key ecosystem players, including traditional banks, e-commerce platforms, and PropTech innovators. This interoperability is vital for Smart City development, which requires financial capabilities to be embedded directly into everyday urban digital infrastructure.

On a practical level, adopting this new architecture does not require a risky, overnight overhaul of existing legacy systems. Companies can execute this transition gradually through the targeted adoption of microservices. This incremental strategy is highly beneficial as it keeps digital transformation costs manageable while guaranteeing that core business activities continue to run without disruption during the migration process.

V. CONCLUSION

This study comprehensively formulates an enterprise architecture that diversifies the revenue model of lending platforms into various intelligently optimized streams. The designed architectural solution addresses previous research gaps by demonstrating that reliance on interest income can be mitigated through the implementation of embedded transaction fees and third-party analytical services. The development of an architecture that separates heavy computational loads from transactional decision-making ensures a drastic reduction in operational and default risks. Leveraging historical data for subscription-based analytical commodities presents an innovative approach to maximizing all digital assets. To strengthen the implementation of the constructed model, future research needs to examine the integration of blockchain-based security protocols in cross-institutional data exchange to ensure user privacy levels meet the latest global financial regulatory compliance standard.

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