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A Proposed Hybrid Conceptual Model of Artificial Intelligence and Enterprise Architecture for Digital Transformation in Banks: An Approach to Improving Business Processes

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Abstract

Digital transformation, as a strategic imperative in the banking industry, necessitates the integration of Artificial Intelligence (AI) and Enterprise Architecture (EA) to enhance business processes. This paper presents a hybrid conceptual model wherein various layers of EA are aligned with AI components. The objective of this model is to augment organizational agility and efficiency through improved decision-making, process automation, and data analytics. Furthermore, by identifying the interconnection points between AI and EA, the optimization of banking loan processes is examined as a practical application. The results indicate that this integration can lead to an improved customer experience, reduced processing time, and increased accuracy in credit assessment. Through this model, banks will be able to respond rapidly to environmental changes and enhance their competitiveness in the market.

Keywords: Enterprise architecture, Artificial intelligence, Machine learning, Digital transformation, E-banking processes.

1 | Introduction

In the current era, digital transformation has become a fundamental pillar of success for organizations, particularly within the banking industry. Faced with various challenges such as rapid changes in customer

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needs, increasing competition, and technological advancements, banks are compelled to re-evaluate their business models and processes. In this context, the integration of Artificial Intelligence (AI) with Enterprise Architecture (EA) emerges as an innovative approach to improve organizational performance and enhance agility.

This paper investigates and presents a hybrid conceptual model of AI and EA for digital transformation in banks. The objective of this model is to improve business processes and create alignment between emerging technologies and the organization's strategic objectives. Considering the significance of AI in data analysis and process automation, this research identifies the interconnection points between AI and EA. It elucidates how this synergy can be leveraged to enhance banking performance.

Thus, the proposed model in this paper can be utilized as a solution for improving e-banking processes and increasing customer satisfaction in the digital age.

2 | Enterprise Architecture

EA is an approach for understanding, engineering, and managing all organizational elements and their interrelationships [1]. It refers to a comprehensive description of an organization and a set of descriptive representations (Models) for articulating an organization, such that these can be produced in accordance with management (Quality) requirements and maintained (i.e., adaptable to change) throughout their proper lifecycle [2]. Architecture frameworks are methods used in architecture modeling, providing a structured and systematic approach to system design [3].

EA frameworks have been developed by governments or the private sector, either with a general-purpose or a sector-specific approach. Examples of EA frameworks developed to date include Federal frameworks (e.g., Federal Enterprise Architecture Framework (FEAF)) [3], [4], The Open Group Architecture Framework (TOGAF) [5], Gartner's methodology, Command, Control, Communications, Computers, Intelligence, Surveillance, and Reconnaissance (C4ISR) [6], Department of Defense Architecture Framework (DoDAF) [7], the Treasury EA Framework (TEAF) [8], the National Institute of Standards and Technology (NIST) EA Model, and other frameworks such as the Iran Enterprise Architecture Framework (IEAF) [9].

3 | Digital Transformation

Digital transformation is a strategic process that involves redesigning business models, changing the way services and products are delivered, and improving operational efficiency through the implementation of digital technologies such as the Internet of Things (IoT), AI, and Blockchain. This transformation necessitates aligning digital capabilities with organizational strategies to bring about fundamental changes in the value chain and process structures [10].

3.1 | Digital Transformation in the Banking Industry

Digital transformation is an organizational change aimed at reinventing the organizational structure and optimizing processes through the implementation of advanced technologies such as Machine Learning (ML) and data analytics. It should be executed in such a way that new technologies act as enablers for the development of new products and services [11]. Accordingly, digital transformation in banking is an approach that involves leveraging emerging technologies to digitize the customer experience, improve data management, and facilitate decision-making processes. In this regard, banks utilize AI and cognitive systems to adapt to environmental changes and achieve agility [10].

This process entails fundamental changes in strategies, organizational structures, and work processes. As a result, banks can adapt themselves to new technologies and enhance their competitiveness.

4 | Artificial Intelligence

According to the High-Level Expert Group (HLEG) on AI definition, AI is recognized as systems that exhibit intelligent behavior by analyzing their environment and taking actions, with some degree of autonomy, to achieve specific goals. Notably, this definition is adaptable to future advancements in the field and, while focusing on ML and Deep Learning (DL), it also encompasses other traditional and innovative AI Methods [12].

This broad definition refers not only to current technologies but also to future advancements in areas such as Artificial General Intelligence (AGI), which aims to simulate all human cognitive abilities. Although achieving AGI is still years (Or even decades) away, focusing on current levels of AI, such as DL algorithms and their applications in various industries like the banking sector, can be instrumental in empowering operational capabilities and enhancing competitiveness.

4.1 | Applications of Artificial Intelligence in the Banking Industry

Methods such as Linear Discriminant Analysis (LDA), logistic regression, naive bayes, and Bayesian networks, along with conventional algorithms like random forest and Support Vector Machine (SVM), are used for credit risk modeling in the banking sector. Additionally, DL techniques such as Artificial Neural Networks (ANNs) and Recurrent Neural Networks (RNN) are utilized to improve the prediction of banking customer behavior [10].

AI is leveraged in the detection and prevention of financial fraud, particularly through the use of Natural Language Processing (NLP). Furthermore, by employing Latent Semantic Analysis (LSA) and semantic indexing, scalable data analysis is performed through tools such as KNIME [13].

Moreover, emphasizing the importance of understanding cause-and-effect relationships between input and output variables to improve the effectiveness of predictions, various ML approaches are applied. Supervised, unsupervised, and reinforcement learning algorithms are utilized for financial forecasting. ML is also applied in financial planning analysis and for providing recommendations in financial plan design. Additionally, Multilayer Perceptron (MLP) neural network algorithms and forest-based methods are employed for accurate data analysis and prediction [14].

5 | Artificial Intelligence and Enterprise Architecture

In the proposed conceptual model, selected layers of EA, including the strategy layer, business layer, data and information layer, application layer, and technology and infrastructure layer, are aligned with corresponding AI components (*Fig. 1*).

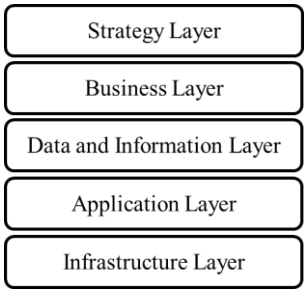

Fig. 1. The enterprise architecture layers utilized in the proposed model.

In this model, EA is utilized as a framework for strategic guidance and alignment, while AI is employed within each layer to create analytical, automation, and decision-making capabilities. The objective of this integration is to enhance organizational agility, scalability, and flexibility (*Table 1*).

Table 1. Alignment of enterprise architecture layers with artificial intelligence components.

EA layer	AI component
Business layer	Decision Support Systems (DSS) and process automation
Data and information layer	ML tools for big data analytics
Application layer	Design of intelligent applications for NLP and customer interaction
Infrastructure layer	Deployment of AI models in cloud infrastructures or distributed environments

5.1 | Integration Points of Artificial Intelligence and Enterprise Architecture

The hybrid conceptual model integrating 'AI and EA' for the digital transformation of banks necessitates identifying common ground and synergies between these two domains. These points are the loci where AI tools, algorithms, and capabilities connect to the various layers of EA, contributing to the transformation of organizational processes, decision-making, and strategy. Identifying and leveraging these integration points in developing roadmaps and action plans enables banks to optimally utilize AI capabilities towards achieving strategic objectives, improving processes, and enhancing customer satisfaction.

Subsequently, these integration points are elaborated within a layer-integration-point-tool-function framework. Each layer has a one-to-many relationship with integration points, and each integration point has a one-to-one relationship with a tool and a function. Furthermore, the relationship between tools and functions is many-to-many, meaning that multiple tools may be utilized to cover multiple functions, and vice versa (*Fig. 2*).

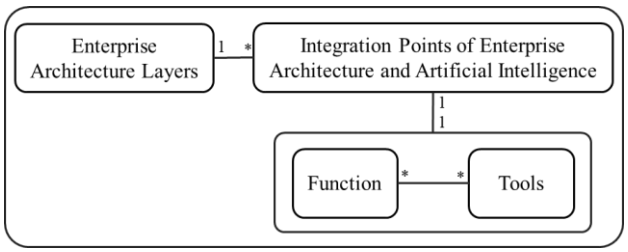

Fig. 2. Alignment of enterprise architecture layers with artificial intelligence integration points.

5.1.1 | Strategy layer

The EA Strategy Layer encompasses overarching goals, digital transformation roadmaps, and strategic planning. AI can contribute to optimizing strategic decisions through extensive data analysis and simulation. (*Table 2*)

Table 2. Strategy layer: Integration points, tools, and functions.

Strategy Layer		
Integration Point	**Tool**	**Function**
Scenario analysis and strategic forecasting	Predictive models and scenario analysis tools	Utilizing AI to simulate various outcomes in different scenarios, e.g., the impact of implementing changes in lending policies on Return on Investment (ROI).
Resource and project portfolio optimization	Optimization algorithms and reinforcement learning	Assisting in decision-making regarding resource allocation to various projects, or optimizing the bank's credit project portfolio based on historical data and predicted patterns.

5.1.2 | Business layer

The Business Layer in EA encompasses various services, business processes, tasks, and activities within the bank. AI can assist in this layer by improving services, optimizing and automating processes, supporting decision-making, and aiding in risk management (*Table 3*).

Table 3. Business layer: Integration points, tools, and functions.

Business Layer		
Integration Point	**Tool**	**Function**
Business process automation	Robotic Process Automation (RPA) and intelligent agents	Connecting RPA to core lending processes (e.g., application submission, initial review, and data processing) to optimize workflow
Process analysis and identification of improvement areas	Machine learning and data analytics	Utilizing AI to analyze the performance of various processes (e.g., credit assessment or resource allocation) and identify bottlenecks and weaknesses. The data obtained helps in modeling processes within the business architecture.

5.1.3| Data and information layer

The data layer in EA is responsible for managing and integrating data across the entire organization. For AI, this layer serves as the data source, and AI utilizes it for analysis, prediction, and decision-making (*Table 4*).

Table 4. Data and information layer: Integration points, tools, and functions.

Data and Information Layer		
Integration Point	**Tool**	**Function**
Creation of an integrated data platform	Data warehouses and big data management systems like Hadoop and Spark	Utilizing enterprise data architecture to integrate and standardize data so that AI algorithms can seamlessly use various data sources (e.g., transactions, credit information, customer records).
Predictive analytics	ML algorithms (e.g., regression, random forest, and neural networks)	Connecting AI analytical models to the organizational database to predict future outcomes (e.g., predicting loan repayment probability or identifying high-risk customers).
Data quality management	Anomaly detection algorithms	Using AI algorithms to identify and resolve issues related to incorrect, duplicate, and missing data, ensuring data quality is maintained in the data layer and AI analyses become more accurate.

5.1.4|Application layer

The application layer in EA encompasses applications and information systems that support business processes. Here, AI can assist applications in creating new capabilities such as recognition, learning, and decision-making (*Table 5*).

Table 5. Application layer: Integration points, tools, and functions.

Application Layer		
Integration Point	**Tool**	**Function**
Integration of AI into Customer Relationship Management (CRM) systems	NLP and sentiment analysis models	Connecting NLP models to CRM systems to analyze customer conversations and provide intelligent responses or identify potential customer issues.
Smart decision support in financial applications	Recommender systems and reinforcement learning	Utilizing recommender systems to suggest suitable products to customers (e.g., proposing loans based on specific customer needs) or using reinforcement learning to optimize financial offerings.
Automation of internal processes with intelligent agents	RPA and AI-powered intelligent agents	Implementing intelligent agents in Enterprise Resource Planning (ERP) and Business Process Management (BPM) systems to perform repetitive tasks, such as document issuance, loan management, or executing complex financial processes.

5.1.5 | Technology and Infrastructure Layer

The Technology and Infrastructure Layer of EA encompasses infrastructures, networks, and information technology systems that support applications and data. This layer provides a foundation for the implementation and execution of AI (See *Table 6*).

Table 6. Technology and infrastructure layer: Integration points, tools, and functions.

Application Layer		
Integration Point	**Tool**	**Function**
Computational infrastructure for AI Model deployment	Cloud infrastructures	Implementing and executing ML models and data analytics in cloud environments for scalability and faster access to computational resources.
Microservices architecture implementation	Docker and Kubernetes	Utilizing microservices architecture for modular and scalable development and management of various AI model components, allowing them to connect to different organizational systems easily.
Security and access management in AI-based systems	Identity and Access Management (IAM) systems and cybersecurity tools	Using ML models to identify security threats and control access in the technology and infrastructure layer.

6 | Proposed Conceptual Model Architecture

The model architecture has been developed based on the extraction of core and common layers of EA from prevalent frameworks, complemented by two vertical layers: AI and Integration. The AI layer features integration points with the horizontal layers of EA. It includes specific tools and functionalities for each integration point, which are developed in a purpose-built manner for each industry. In (*Tables 2-6*), the AI integration points, corresponding tools, and their functionalities for each of the EA layers have been extracted at a high level of abstraction, with a particular focus on the banking industry (See *Fig. 3*).

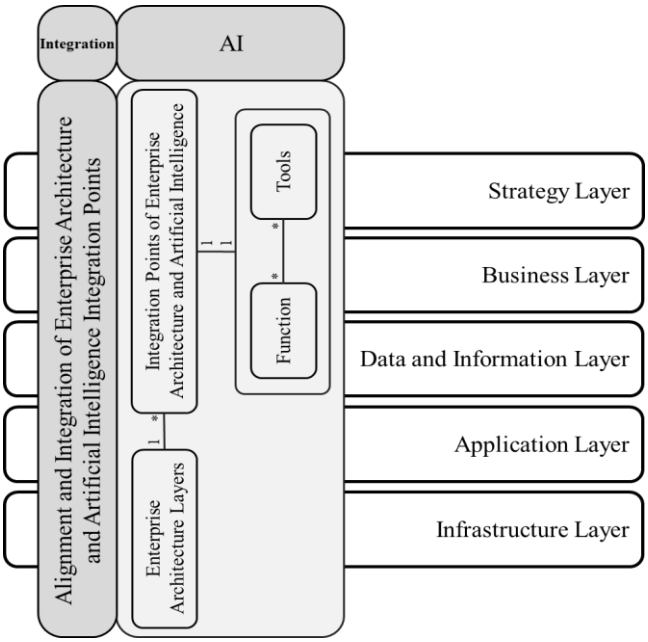

Fig. 3. Proposed conceptual model architecture.

7 | Research Applicability

In the present study, the elucidation of applicability is carried out to clarify how the proposed conceptual model can be implemented, and also to enable a more precise qualitative evaluation through the provision of a questionnaire.

To this end, the Business Layer has been selected as the sample layer, and the lending process has been selected as one of the most critical banking processes, which encompasses a set of internal and external banking processes.

7.1 | Lending Processes

Lending processes refer to a set of activities and operations that include receiving loan applications from customers, customer credit assessment, processing financial information, approving or rejecting applications, determining interest rates, collateral management, resource allocation, creating repayment schedules, disbursing, repaying, and monitoring repayment. Due to their complexity and reliance on risk assessment, customer data analysis, and coordination among various bank departments, these processes require a cohesive structure and advanced tools.

7.1.1 | Existing challenges in lending processes

In traditional settings, banking and lending processes often face the following challenges:

Lengthy processing time: Reviewing applications and documents is time-consuming due to a lack of automation and data aggregation.

High risk in credit assessment and repayment prediction: Due to the absence of intelligent predictive models, incorrect credit decisions may be made.

Complexity in collateral and guarantee management: The lack of integrated systems can lead to inconsistencies in collateral registration and tracking.

Customer dissatisfaction: Due to lengthy review times and a lack of transparency in the process, customer satisfaction levels decrease.

7.1.2 | Role of the proposed conceptual model in improving lending processes

The proposed conceptual model, which integrates EA and AI, can contribute to enhancing performance and efficiency at every stage of the lending process. In this section, some aspects of this model that directly impact lending processes are highlighted.

Table 7. Intersection of enterprise architecture and artificial intelligence in the business layer/loan origination process.

Business Layer/Lending Processes		
Integration Point	**Tool**	**Function**
Optimizing application intake and evaluation processes	NLP and automated text processing systems	Rapid analysis and review of loan applications and extraction of key information from submitted documents (Such as financial statements or credit reports).
	ML	Analysis of historical customer data patterns and identification of patterns related to successful or unsuccessful repayments.
	Decision tree and random forest algorithms	Initial validation and evaluation of applications.

Table 7. Continued.

Business Layer / Lending Processes	Business Layer / Lending Processes	Business Layer / Lending Processes
Intelligent customer credit assessment	Regression Models and Neural Networks	Analysis of credit data and prediction of customer risk. These models can consider parameters such as repayment history, income, work history, and current debt levels.
	Scoring systems based on logistic regression models or deep neural networks	Calculation of credit scores and prediction of repayment probability.
Decision support for loan allocation	Recommender systems	Recommending appropriate interest rates, repayment periods, and resource allocation conditions based on customer information and similar patterns. These systems can use collaborative filtering and content-based filtering methods.
	Reinforcement learning	Finding the best resource allocation strategy and optimizing the bank's loan portfolio based on market data and environmental changes.
Automation of operational and managerial processes	RPA	Prediction of future customer behavior and repayment risk analysis.
	Intelligent agents	Analysis of the effects of different economic conditions on repayment performance and collateral management. Use of Monte Carlo simulations in this method.
Risk analysis and collateral management	Predictive models such as Markov chain models or RNNs	Prediction of future customer behavior and repayment risk analysis.
	Scenario analysis	Analysis of the effects of different economic conditions on repayment performance and collateral management. Use of Monte Carlo simulations in this method.

7.1.3 | Integration of the proposed conceptual model with the bank's enterprise architecture

EA, as a framework for aligning business goals, technology, and processes, plays a fundamental role in implementing this conceptual model within the lending processes. The integration of EA with AI tools across various layers (Such as strategy, business, data and information, application, and technology and infrastructure) is expected to yield the following results:

I. Increased processing speed for loan applications. Reduction in human error in risk assessment and management.

II. Improved accuracy in predicting customer credit behavior.

III. Enhanced customer satisfaction through greater transparency and faster processing.

IV. Reduced operational costs through process automation.

Furthermore, during the implementation of this model, challenges such as organizational change management, compliance with laws and regulations, ensuring data quality, and systems integration may arise. Therefore, the design and implementation of the model must consider these challenges and be carried out in collaboration with various departments within the bank.

8 | Evaluation of the Proposed Conceptual Model

A qualitative evaluation, conducted through a questionnaire focusing on expert opinions, assessed the effectiveness of the proposed conceptual model on selected processes (Banking facilities). The results of the questionnaire indicated that the objectives of developing the conceptual model were achieved, with an average

quantitative score of 3.71 and a qualitative description of "Desirable". The reliability of the questionnaire, calculated using Cronbach's Alpha in SPSS-16, was 0.81.

Table 8. Introduction of the expert panel.

Expert Panel (Total of 16 Respondents)		
Educational Level	**Number of Respondents**	**Percentage of Total**
Master's degree	11	68%
Doctorate and PhD candidates	5	32%

9 | Conclusion

The findings of this study demonstrate that the integration of AI and EA plays a pivotal role in the digital transformation of the banking industry. The implementation of the proposed conceptual model can contribute to the enhancement of business processes within banks. AI, with its capabilities in data analysis and ML, enables more intelligent and faster decision-making, while EA serves as a framework for structuring and coordinating these changes.

By focusing on the strengths of these two domains, banks can improve customer experiences, reduce application processing times, and increase the accuracy of credit assessments. Ultimately, this integration helps banks respond to rapid environmental changes and maintain a leading position in the market. To succeed on this path, banks must pay special attention to fostering organizational culture change, developing employee skills, and investing in new technologies. Moreover, formalizing dedicated roles within the organizational structure, such as a Chief Artificial Intelligence Officer (CAIO) to champion AI strategy and AI Integration Architects (Or specialists) to ensure seamless alignment with EA, will be crucial for effectively harnessing AI's potential and embedding these capabilities deeply within the organization. This approach can also serve as a successful model for other industries.

To fully realize the potential of integrating AI with EA and ensure its alignment with strategic business objectives, defining and institutionalizing specialized roles within the organizational structure is essential. These roles are not only responsible for guiding, designing, and implementing AI solutions but will also serve as a bridge between technical teams, business units, and EA leaders. The table below outlines some key proposed roles, along with a description of their relationship with the aforementioned domains. It is important to note that the exact titles and scope of responsibilities for these roles may vary depending on the size, maturity, and specific structure of each organization; however, their core responsibilities are vital for the success of AI and EA initiatives (See *Table 9*).

Table 9. Roles and their relationships.

Proposed Role	Relationship with AI	Relationship with EA	Relationship with Organizational Structure	Relationship with the EA Project
Chief Artificial Intelligence Officer (CAIO)	Develops and leads the overall AI strategy for the organization, oversees AI initiatives, promotes a data-driven and AI-centric culture, and manages AI risk and ethics.	Ensures AI strategy aligns with EA and overarching business goals. Collaborates with the EA team to define AI-related standards.	Senior leadership role, typically reporting to the CEO or CIO. Establishes and leads an AI Center of Excellence (CoE) if necessary.	Provides strategic vision for incorporating AI capabilities into the target architecture. Supports and allocates resources for AI-related EA initiatives.

Table 9. Continued.

Proposed Role	Relationship with AI	Relationship with EA	Relationship with Organizational Structure	Relationship with the EA Project
AI integration architect/specialist	Designs how AI solutions integrate with existing systems and processes. Selects appropriate AI platforms and tools. Provides technical oversight for AI implementation.	Translates AI requirements into architectural components. Ensures AI solutions comply with EA principles and standards. Defines AI integration patterns.	Can be part of the EA team, AI CoE, or product development teams. Works closely with AI developers and enterprise architects.	Actively participates in designing the application, data, and technology layers of EA, considering the requirements of intelligent systems. Develops technical integration solutions.
EA	Understands AI capabilities and limitations to include it in technology and business roadmaps. Assesses AI's impact on various architectural layers.	Develops, maintains, and governs the EA framework. Ensures alignment, standardization, and integration across the organization.	Typically, in a centralized EA unit or part of the IT/Strategy department. Collaborates with all business and technology units.	Leads and manages the project to develop or update the EA. Defines and prioritizes architectural initiatives, including those related to AI.
Data scientist/ AI engineer	Develops, trains, deploys, and maintains AI models. Prepares and analyzes data. Evaluates model performance.	Implements AI solutions according to frameworks and standards defined by enterprise architects and AI integration architects.	Member of specialized AI teams, CoEs, or business units requiring advanced analytics.	Provides technical input on the feasibility, required resources, and challenges of implementing AI models within the defined EA framework.
Business process owner	Identifies opportunities for leveraging AI in process optimization. Provides business requirements for AI solutions. End-user and evaluator of AI solutions.	Defines process requirements that the EA (And AI within it) must support. Validates architectural models from a business perspective.	Located within various business units of the organization. Key stakeholder for EA and AI projects impacting their processes.	Provides business and process requirements. Participates in defining the desired state of processes with AI assistance and validates related architectural designs.
Steering committee /governance Body	Oversees the AI project portfolio, prioritization, budget, and resource allocation. Ensures alignment with strategy and manages overarching risks.	Oversees the EA program, approves target architectures and roadmaps. Resolves conflicts and makes decisions on major architectural issues.	Composed of senior executives from various business and technology units. Accountable for the success of strategic programs like EA and AI.	Provides final approval for key EA project plans and deliverables. Ensures support and participation from various units in executing the architecture roadmap, including AI initiatives.

I. Collaboration: Success in this domain heavily depends on effective collaboration among these roles and other stakeholders within the organization.

II. Skills: Developing the necessary skills within teams to fill these roles, whether through internal training or hiring specialists, is crucial.

III. Agility: The structure and roles should be designed to allow for rapid responses to technological changes and evolving business needs.

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