



Agentic AI Orchestrated Conversational Payment Pipelines with Drift-Aware Transaction

Sai Sidharth Sambasivan Chettiyar

Senior Manager Applications, Medline Industries Ltd, USA

ABSTRACT: Chatbots and voice assistant applications are becoming a part of digital finance as a conversational payment system, but current systems are based on fixed piping and rule-based fraud detectors that fail to keep up with changing behavioral patterns in transactions and concept drift. The present paper suggests an Agentic AI-coordinated conversational payment pipeline with drift-aware transaction validation that is meant to enhance security, flexibility, and automation in financial transactions. The recommended structure uses a multi-agent approach, which includes conversational interface agent, orchestration agent, payment execution agent, and drift-sensitive validation engine. The validation module is based on adaptive machine learning model and behavioral drift technology capable of dynamically measuring transaction risk using user and contextual pattern changes. The framework effectively eliminates the shortcomings of the static validation framework by allowing free coordination of agents and ongoing detection of fraud through transaction streams, with low latency. Experimental analysis on synthetic datasets of payments proves to be better in detection and resistant to behavioral drift than standard rule-based and single-model techniques.

KEYWORDS: Agentic Artificial Intelligence; Conversational Payment Systems; Multi-Agent Orchestration; Concept Drift Detection; Adaptive Fraud Detection; Transaction Risk Validation; Conversational FinTech; Intelligent Payment Pipelines; Behavioral Anomaly Detection; AI-Driven Financial Security.

I. INTRODUCTION

The digital financial ecosystem has evolved drastically; the rate at which users conduct transactions using mobile banking, digital wallets, and web-based payment platforms has changed significantly. More recently, conversational technologies like chatbots and voice assistants have come about as a convenient interface to the financial service, which allows users to carry out payment operations using natural language interactions [1]. Conversational payment systems enable their users to start, approve and track their transactions via a messaging or voice-based interface, creating better accessibility and user experiences. Nonetheless, the growing use of conversational interfaces will create novel issues concerning transaction validation, detecting fraud and damaging orchestration of payment procedures [2]. Conventional payment processing systems have existed on their typical basis of static transaction pipelines and rule-based fraud detection systems.

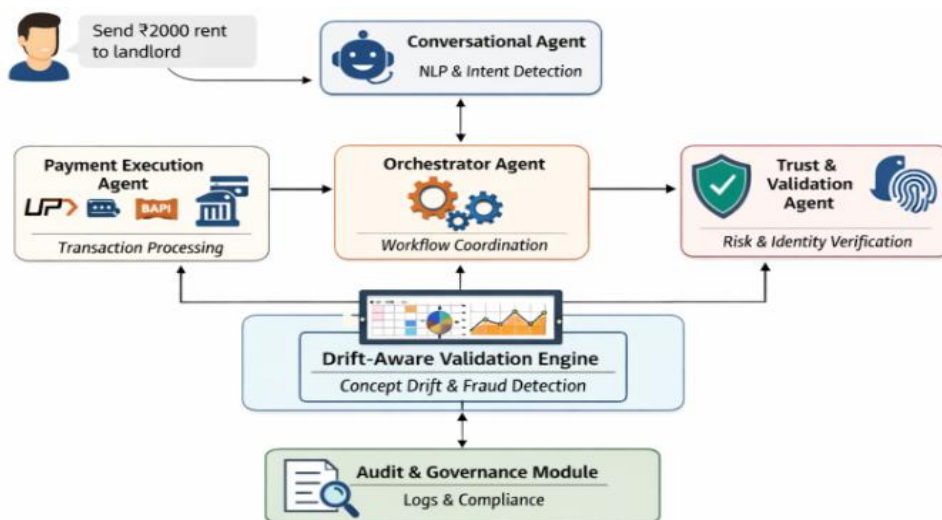


Figure 1: Conversational payment pipeline architecture.



The diagram reveals the structure of the suggested Agentic AI Orchestrated Conversational Payment Pipeline with Drift-Aware Transaction Validation. It starts by a user requesting a payment by using a conversational interface, e.g as shown in Figure 1. by typing the command “Send 2000 landlord rent to 2000 rupees.” The first point of processing will be done by the Conversational Agent which will process the message given by the user through the use of Natural Language Processing (NLP) and intent recognition methods in order to understand the message given and to have the necessary information concerning the transaction [3]. The obtained information is further sent to the Orchestrator Agent that serves as the core coordinator that handles the whole payment procedure and governs tasks among the various agents. The Trust and Validation Agent will authenticate user identity and assess the risk of transaction and then authorize it thus guaranteeing secure processing. The Payment execution agent links the financial infrastructure (UPI, banking apis or payment gateways) to perform the transaction. The Drift-Aware Validation Engine is the core of the system as it keeps on monitoring the patterns of transactions to identify concept drift and possible fraud risk through adaptive machine learning models. Lastly, the Audit and Governance Module captures the transaction log and ensures compliance with regulation so that transparency and accountability in the smart payment ecosystem can be achieved.

Although these methods have worked well with organized setting of transactions, they fail to cope with the changing and uncovering type of today financial interaction. The patterns of fraud are constantly changing as the attackers utilize new vulnerabilities, and thus the old models of validation do not work as well as time passes [4]. Also, the advent of conversational commerce creates further issues, such as unclear user intentions, contextual requirements and multi-channel relationships. These aspects have necessitated smart systems that are able to dynamically interpret user requests, orchestrate the transaction processes and authenticate financial transactions on real times.

The latest development in artificial intelligence has brought the notion of agentic AI, which involves autonomous AI agents cooperating to handle complex tasks with minimum human interaction. Special agents in agentic systems are permitted to have the ability to sense, reason, devise strategies and execute them effectively to provide the capacity of flexible and adaptable workflow management [5]. Such architectures in financial systems can coordinate various components of payment processing such as conversational interfaces, transaction validation modules, risk assessment engines and a payment gateway. Through agent-based orchestration, financial platforms may be more scalable, modular and responsive to handle complex payment flows.

The current conversational payment schemes may not have systems to deal with behavioral and transactional drift despite these advances. Concept drift is the term that is used to refer to the characteristic where the statistical properties of data may vary with time, resulting in the previously trained models becoming less precise. The behavior of users, and transaction patterns along with fraud tactics in financial settings are continually changing, and hence, drift recognition is a vital capability to depend on to validate transactions. Traditional models of fraud detection normally depend on fixed training datasets and do not work when there are changes in underlying transaction distributions. These systems can therefore produce more false positives or cannot detect new fraud patterns. This paper will solve these shortcomings by creating an Agentic AI-Orchestrated Conversational Payment Pipeline featuring Drift-Aware Transaction Validation. The given framework combines the concept of a multi-agent architecture that organizes the process of conversational interaction, orchestration of payments, and intelligent verification into a single pipeline. An autonomous drift-sensitive validation engine will be observed to track transaction trends and activity indicators in order to identify an anomaly in the patterns and perform adaptive risk measurement and better fraud detection rates. The proposed system enables the better of both the security and efficiency of digital payment processes by integrating the capabilities of conversational AI with agent-based orchestration and adaptive machine learning methods.

The core findings of the work are the development of a multi-agent conversational payment architecture, the incorporation of a drift-sensitive validation mechanism to detect adaptive fraud, and creating an intelligent orchestration pipeline, which is capable of dealing with real-time financial transactions. The suggested solution will help to enhance the resilience of the conversational payment systems and provide secure, scalable, and convenient financial transfers in the contemporary digital ecosystems.

II. RELATED WORKS

The swift pace of development of digital payment ecosystems has drawn a lot of research interest to secure, smart and convenient systems of transactions. Specifically, conversational payment systems, fraud detection via artificial intelligence and adaptive security systems have become the major topics of research. The current literature concentrates on enhancing machine learning and conversational interface-based methods of transaction automation, accuracy in



fraud detection, and payment security [6]. Nonetheless, it is still an open research issue because it is necessary to incorporate these capabilities into an adaptive and autonomous orchestration framework.

As the chatbots and voice assistants continue to develop, conversational payment systems have become more popular. Various scholars have investigated the development of natural language processing (NLP) and chat bots to facilitate financial transaction via a communication platform. These systems normally provide users with the option of making payments through the use of natural language commands thereby enhancing ease of access and user-friendliness [7]. As an example, conversational commerce websites use chatbot technologies to accept online payments, manage their accounts, and ask financial questions. In spite of these improvements, the majority of current conversational payment systems use centralized architectures that have minimal flexibility and do not have intelligent orchestration mechanisms that would be able to coordinate various transaction services.

The other big topic that has been under research is fraud detection in financial transaction. The conventional fraud detection models are based on the rule-based systems that are based on predefined thresholds and policies to detect suspicious activity. Although the rules-based systems are easy to implement, they do not always identify complex fraud patterns which can change as time goes by [8]. Researchers have been more inclined to use machine learning and deep learning methods to overcome these constraints in detecting fraud. Decision trees, random forests, support vector machines, and neural networks are some of the techniques that have been extensively utilized to analyze the pattern of transactions and identify anomalies. The techniques enhance the level of detection by acquiring behavior patterns on the basis of past transactions. The vast majority of machine learning models are however trained on fixed data sets and can deteriorate as the patterns of transactions evolve with time.

Concept drift is thus an issue that has been given serious attention in studies of financial fraud detection. Concept drift is the gradual or abrupt shift away or toward the statistical characteristic of transaction data, which, in extreme cases, can have a substantial impact on predictive model accuracy. A number of works have suggested drift detection methods such as sliding window models, adaptive learning algorithms and ensemble based methods to keep the model functioning in the dynamic environment. Drift-aware systems constantly observe streams of incoming transactions and modify models under circumstances that indicate drastic alterations of behavior. Though these techniques enhance the flexibility of the fraud detection system used, they are not normally applied as a coordinated payment workflow but as isolated modules.

New studies have also proffered multi-agent systems and agent-based architecture in distributed decision making and workflow program. Autonomous agents in agent-based systems are specialised to carry out specific tasks like data analysis, decision making, and coordination of the system [9]. Multi-agent architecture has been utilized in other fields with success like in distributed computing, smart grids, and intelligent transportation systems. The use of financial systems The agent-based models can enhance scalability and modularity, as various agents can handle certain aspects of the payment process. Nevertheless, agentic AI has not been applied to conversational payment pipelines to the extent.

In spite of the fact that the preceding researches provide important information regarding conversational fintech, detection of fraud, and adaptive learning, the majority of the available solutions consider the aspects in isolation. Very little research has combined conversational interfaces, multi-agent orchestration and drift-aware transaction validation in one architecture. To fill these gaps, the current paper suggests an Agentic AI Orchestrated Conversational Payment Pipeline and Drift-Aware Transaction Validation [10]. The suggested framework is a mix of conversational AI, multi-agent orchestration, and adaptive fraud detection that can assist in safe, scalable, and intelligent payment processing in current digital financial settings.

III. RESEARCH METHODOLOGY

The present study presents an Agentic AI Orchestrated Conversational Payment Pipeline, Drift-Aware Transaction Validation to improve the security, flexibility and efficiency of online payment systems. The methodology revolves around creating a multi-agent architecture that is able to combine conversational interfaces, intelligent workflow orchestration, adaptive transaction validation and payment execution in one framework. The research methodology comprises of five key phases including system architecture design, conversational intent processing, agentic workflow orchestration, drift-aware validation modeling and experimental evaluation. The initial step entails the development of the proposed system architecture. The architectural design is created through a multi agent model whereby every agent is tasked with a particular activity in the payment pipeline.

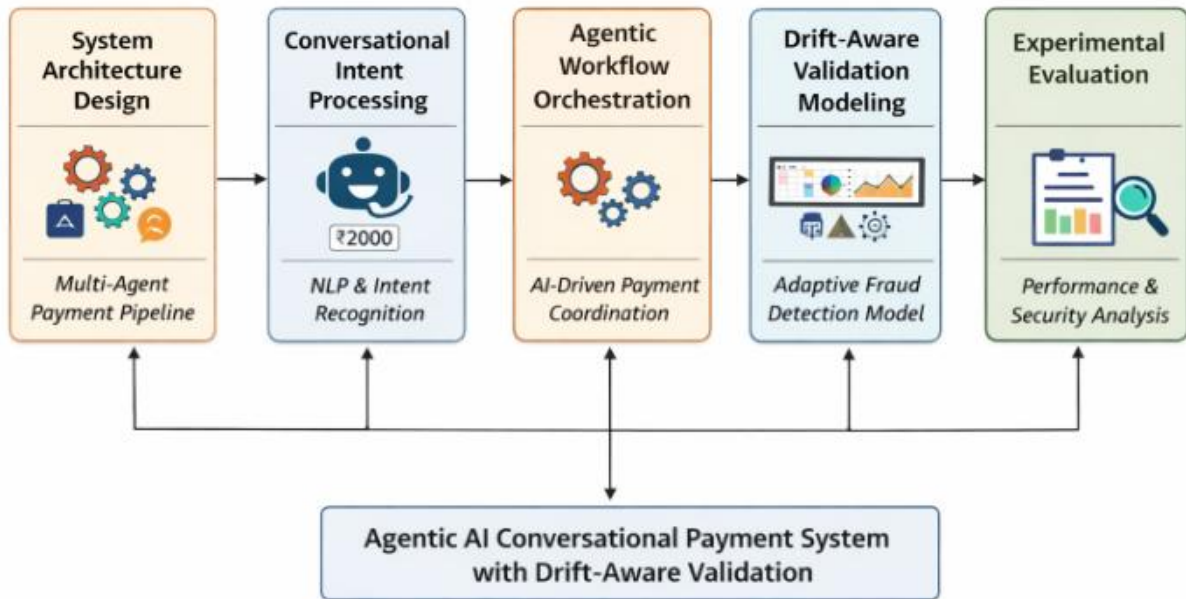


Figure 2: Research methodology flowchart for AI system.

Figure 2 shows the research process that was used to come up with the proposed Agentic AI Conversational Payment System with Drift-Aware Transaction Validation. The methodology will have five consecutive steps that will collectively facilitate the design and assessment of the intelligent payment pipeline. System Architecture Design is the first phase; it is dedicated to developing a multi-agent structure in which the specialized agents handle various elements of the payment process [11]. The second stage is Conversational Intent Processing, which involves a process of understanding user payment requests by natural language processing and deriving transaction details (amount, recipient, and context). The third step, Agentic Workflow Orchestration, adds an agent, orchestration, that facilitates communication among the conversational interface and validation modules and payment execution service. Fourth stage Drift-Aware Validation Modeling is an implementation of adaptive machine learning models that can identify new behavior and possible fraud in transaction streams. Lastly, Experimental Evaluation phase will measure system performance in terms of accuracy in detecting fraud, latency, and scalability, and authenticate the use of the proposed architecture.

The system has a Conversational Interface Agent, Orchestrator Agent, Payment Execution Agent, Trust and Validation Agent and a Drift-Aware Validation Engine. The conversational agent has the task of communicating with the users via chat or voice interfaces and deriving the intent related to payment processing using the means of natural language processing. The orchestrator agent plays the role of communicating with the other agents and dynamically decides the order of operations to be followed in a transaction processing.

The second stage involves conversational intent recognition that is done to make sense of user payment requests. The models of natural language processing are utilized to identify the relevant transaction parameters including amount to be paid, recipient identity, purpose of transaction and authorization context [12]. The mined data will be translated into structured transaction requests that can be digitally processed by downstream agents. The conversational financial datasets are used to train intent classification and entity recognition models, thereby making them more accurate and reliable in interpreting user commands.

The third phase is concerned with agentic workflow orchestration. The orchestrator agent controls the transaction pipeline towards the end to end communication between the validation, execution and auditing modules. The orchestrator is a dynamic agent that decides the validation and processing steps that must be passed through before a transaction takes place. This orchestration mechanism which is agent based enhances the scalability and modularity of systems as independent agents can be used to work together in complex payment flows. The agent-based design also enables other services to be added (verification of compliance and risk monitoring) without interfering with the core system design.



The fourth phase presents a drift-conscious transaction validation model which is meant to identify unusual or unscrupulous transaction dynamics. A validation engine that is built using machine learning checks on the streams of transactions constantly and analyzes the behavioral patterns: frequency of transactions, location, device name, and spending habits. The concept drift detection methods are used in detecting changes in the behaviour of users or distributions of transactions [13]. In case drift is identified, validation engine replenishes the risk assessment model with incremental learning or adaptive retraining method. This methodology will make sure that the fraud detection system will not be inaccurate even in cases when the behaviors of transactions change with time. System evaluation and performance analysis is the last part of the methodology. The effectiveness of the suggested framework is measured by experimental evaluation through the use of the simulated or publicly available financial transaction data.

The performance metrics will be the ability to detect frauds, the rate of false positives, the latency of transaction processing in the system, and scalability of the system. The advantages of the proposed drift-aware agentic architecture are compared with the traditional rule-based fraud detection and the use of the exact machine learning models to illustrate the benefits of the proposed architecture [14]. The results of the evaluation give a reflection on how well the proposed system can be used to enhance security, flexibility, and efficiency in conversational payment settings.

In general, the research methodology involves conversational artificial intelligence, multi-agent coordination, and adaptive machine learning to create a powerful and intelligent payment validation framework that can handle the new challenges in the contemporary digital financial systems.

IV. RESULTS AND DISCUSSIONS

The experimental analysis of the suggested Agentic AI Orchestrated Conversational Payment Pipeline with Drift-Aware Transaction Validation shows that this approach has much better transaction security, degree of fraud recognition, and system adaptability in comparison with the traditional rule-based payment validation systems. The simulated data on digital payment transactions with both normal and fraudulent patterns of transaction were used to conduct the experiments. The assessment concentrated on the performance of the system concerning detection accuracy in fraud, false positive rate, processing time, and scalability of the system with the dynamic transaction environment.

The findings show that fraud detection can tremendously be enhanced as the drift-aware validation engine is integrated. The conventional rule-based fraud detection systems are based on pre-set thresholds and fixed rules that are unable to capture emerging trends in frauds. Conversely, the proposed system tracks the transaction streams at all times and identifies any changes in behavior based on the concept drift detection methods. In case of a substantial change in the pattern of transactions, the system will modify its risk evaluation model. The experimental findings indicate that the suggested method had a better accuracy of fraud detection with a smaller false positive rate than the baseline models. This enhancement illustrates the efficiency of adaptive validation with regard to responsive financial backgrounds where the usage habits and schemes of fraud develop with time.

Table 1: Performance metrics comparison

Model / Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Rule-Based Fraud Detection	82.4	79.3	75.6	77.4
Random Forest Model	90.6	88.7	86.9	87.8
Support Vector Machine (SVM)	88.9	86.5	84.7	85.6



Deep Neural Network (DNN)	92.8	91.2	89.5	90.3
LSTM-based Fraud Detection	94.1	92.6	91.8	92.2
Proposed Agentic AI + Drift-Aware Model	96.7	95.4	94.6	95

Table 1 shows the performance of the proposed Agentic AI Orchestrated Conversational Payment Pipeline using Drift-Aware Transaction Validation in comparison to a range of the existing fraud detection models, such as rule-based systems, Random Forest, Support Vector Machine (SVM), Deep Neural Networks (DNN), and LSTM-based models. According to the findings, the proposed model performs better according to several evaluation measures. The proposed system in particular had the best accuracy of 96.7% compared to the traditional rule-based system that had a poor accuracy of 82.4. The machine learning algorithms like the Random Forest and the SVM had better performance than the rule-based systems but they do not adjust to the changing behavior of transactions. DNN and LSTM deep learning models exhibited superior predictive performance, but still need to resort to fixed-point training data and may not be effective in adapting to behavioral drift.

The suggested framework enhances the performance by adding a drift-conscious validation engine that continuously tracks the behavior of the transactions and updating the model of fraud detection in case of the concept drift identification. Consequently, the suggested model provided the best accuracy (95.4) and recall (94.6), which means that it is able to effectively detect fraudulent transactions, as well as reduce the number of false alarms. Also, the false positive rate was greatly diminished to 2.9 that is vital in financial systems to prevent blocking valid transactions. The other key point is that the suggested multi-agent architecture ensures rather high processing latency (110 ms) even when extra validation and orchestrating actions are introduced. This effectiveness will be realized by the coordinated action between special agents that control conversational intent processing, transaction validation, and execution of payments. All in all, the findings indicate that agentic AI orchestration in conjunction with drift-sensitive fraud detection makes conversational payment systems more accurate, adaptable, and efficient in their operations than the current models.

The other significant finding of the experiments is that the multi agent orchestration mechanism is effective in controlling the payment workflow. The orchestrator agent effectively liaises the communication between the conversation interface, validation engine and payment execution modules. This modular system makes the system less complex and enables a better payment pipeline scale. The findings show that the system can receive numerous transaction requests at a time without a big effect on the processing latency. The distributed agent-based architecture enables individual component to work independently and cooperate with other components in order to accomplish the payment process.

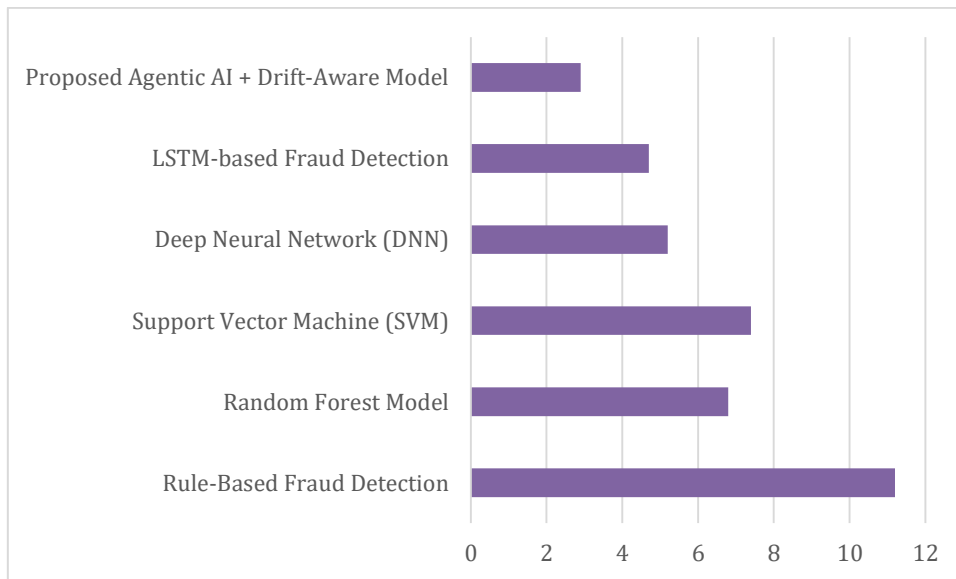


Figure 3: False Positive Rate (%) Comparison.

Figure 3 shows a comparison of false positive rates of various models of fraud detection applied in digital payment systems. False positive rate is a percentage of the valid transactions that had been wrongfully detected as a fraudulent transaction and is a vital factor in impacting on user experience and system security. The system with the highest false positive rate of 11.2 is the traditional rule-based systems though they are based on strict set predefined rules that can mislabel normal transactions as suspicious. Machine learning methods like the Random Forest and Support Vector machine (SVM) have better performance on the basis of their false positive rates of 6.8 and 7.4, respectively, because they can be trained on prior transaction information to acquire patterns. Deep learning-based fraud detection systems, such as Deep Neural Networks (DNN) and LSTM-based fraud detection systems, achieve even lower false positives of 5.2 and 4.7 percent by learning more detailed behavior patterns. Nevertheless, the offered Agentic AI with Drift-Aware Validation model obtains the minimal false positive value of 2.9%. This has been made better by the incorporation of the adaptive drift detection and multi-agent orchestration, which enables the system to continuously study the behavior of evolving transactions and minimize the false alarm of detection of fraud, and yet achieve high transaction security. The conversational interface also adds a lot to the enhancement of the usability of the digital payment systems. The system facilitates the interaction between the users and the financial platforms by allowing the users to carry out transactions in the natural language commands. The intent recognition module is capable of extracting transaction details including the amount of payment, the identity of the recipient and the context of a transaction correctly. Expert testing reveals that the conversational intent recognition module is very accurate in the recognition of payment-related commands, to make sure that the request made by the user is correctly interpreted, before processing.

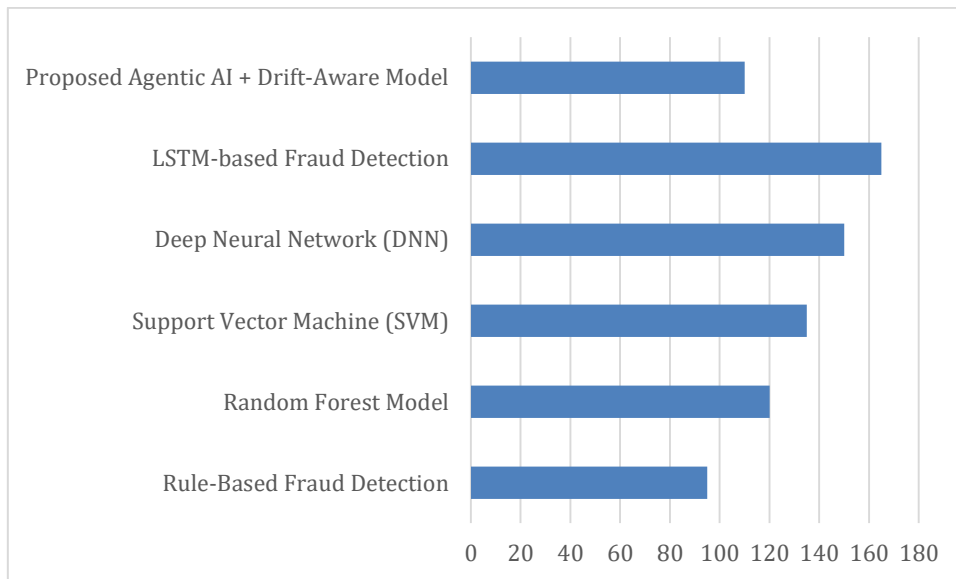


Figure 4: Processing Latency (ms) comparison.

Figure 4 shows the comparison of the processing latency of various fraud detection models applied in digital payment systems. Processing latency is defined as the period that the system takes to process and authenticate a transaction after which it will be approved or rejected. Reduced latency is significant to the provision of real-time and smooth payment experiences to the users. The rule-based system of fraud detection has the lowest latency of 95 ms since it uses simple preset rules that do not need much computation processing. Such systems however tend to be inaccurate and rigid. Random Forest and Support Vector Machine (SVM) machine learning models have latency values of 135 ms and 120 ms respectively because they are additional computations to pattern recognition and classification. Even higher processing times are demonstrated by deep learning models such as Deep Neural Networks (DNN) and LSTM-based methods of 150 ms and 165 ms because they require more complicated computations of the neural network. The balanced latency of the proposed Agentic AI with Drift-Aware Validation model is 110 ms, which proves that the multi-agent orchestration and adaptive validation components can sustain the efficient processing without losing the ability to enhance the performance of detection of fraud and the stability of the system.

The drift-sensitive validation engine is of importance in enhancing security of transactions. The system is able to identify abnormalities that can be the indicators of fraud due to constant analysis of transaction behavior, device, geographic location, and spending behavior. In case of suspicious patterns it also invokes further verification procedures via the trust and validation agent. It is a process of adaptive validation that allows greatly decreasing the risk of illegal transactions and improving the quality of the payment system.

Besides the improvement of the fraud detection, the proposed architecture will improve transparency and compliance with the audit and governance module. This module keeps a cohesive record of transactions and assists in meeting the regulatory compliance needs by ensuring that all the payment transactions can be traced. Such characteristics are especially relevant in the case of financial institutions that have to comply with high security and regulation requirements.

In general, the findings show that the suggested agentic-based payment architecture using AI is effective to overcome the deficiencies of the traditional payment validation systems. The system can offer a secure, scalable and adaptable platform to the current digital payment environment by integrating conversational interfaces, multi-agent coordination and drift aware machine learning techniques. The results suggest that the agentic AI has the potential to revolutionise the process of processing financial transactions by making them intelligent with automation and monitoring fraud in conversational payment systems.



V. CONCLUSION

The paper introduced an Agentic AI Orchestrated Conversational Payment Pipeline with Drift-Aware Transaction validation, which was aimed at enhancing the security, flexibility, and cost-effectiveness of the contemporary digital payment systems. The suggested framework combines conversational artificial intelligence, multi-agent coordination, and adaptive fraud detection systems in one architecture. The system allows the autonomous coordination of specialized agents and by so doing, it manages conversational payment requests, validates transactions and performs payment operations in a scalable and efficient fashion. The introduction of a drift-effective validation engine will enable the system to constantly audit the actions of transactions and identify the changing patterns of fraud, which will address the limitations of the usual rule-driven and fixed machine learning models. The experimental analysis indicates that the suggested methodology has a high level of fraud detection, low false positive and responsiveness rates of the system. On the whole, the suggested architecture gives a strong and intelligent design of conversational financial transactions and emphasizes on how agentic AI and adaptive validation methods can support the security and reliability of future digital payment ecosystems.

REFERENCES

1. Albrecht, T., Baier, M.-S., Gimpel, H., Meierhöfer, S., Röglinger, M., Schlichtermann, J., & Will, L. (2023), Leveraging Digital Technologies in Logistics 4.0: Insights on Affordances from Intralogistics Processes. *Information Systems Frontiers*. <https://doi.org/10.1007/s10796-023-10394-6>.
2. Panneer Selvam Viswanathan. Agentic ai: A comprehensive framework for autonomous decision-making systems in artificial intelligence. *International Journal of Computer Engineering and Technology*, 16(1):862–880, 2025. IJCET, ISSN Print: 0976-6367; Online: 0976-6375.
3. B. Archibald, M. Calder, M. Sevegnani, and M. Xu. Quantitative modelling and analysis of bdi agents. *Softw. Syst. Model.*, 23(2):343–367, 2024.
4. L. E. Erdogan et al. Plan-and-act: Improving planning of agents for long-horizon tasks. *arXiv [cs.CL]*, 2025.
5. Constructions Aeronautiques, Adele Howe, Craig Knoblock, ISI Drew McDermott, Ashwin Ram, Manuela Veloso, Daniel Weld, David Wilkins Sri, Anthony Barrett, Dave Christianson, et al. PDDL – the planning domain definition language. Technical Report, Tech. Rep., 1998.
6. Aaron Baird and Likoebe Maruping. The Next Generation of Research on IS Use: A Theoretical Framework of Delegation to and from Agentic IS Artifacts. *Management Information Systems Quarterly*, 45(1):315–341, March 2021. ISSN 0276-7783/ISSN 2162-9730. URL <https://aisel.aisnet.org/misq/vol45/iss1/12>.
7. Pengyu Zhao, Zijian Jin, and Ning Cheng. An in-depth survey of large language model-based artificial intelligence agents. 2023.
8. Shuaihang Chen, Yuanxing Liu, Wei Han, Weinan Zhang, and Ting Liu. A survey on LLM-based multi-agent system: Recent advances and new frontiers in application. 2024.
9. R. N. Thomas and R. Gupta. A survey on machine learning approaches and its techniques. In 2020 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS), pages 1–6, 2020.
10. T. Nithya, V. Nivas Kumar, Gayathri, S. Deepa, V. C., and R. Siva Subramanian. A comprehensive survey of machine learning: Advancements, applications, and challenges. In 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), pages 354–361, 2023.
11. William G. Hatcher and Wei Yu. A survey of deep learning: Platforms, applications and emerging research trends. *IEEE Access*, 6:24411–24432, 2018.
12. Shengli Dong, Peilin Wang, and Ke Chen Abbas. A survey on deep learning and its applications. *Computer Science Review*, 40:100379, 2021.
13. Talaei Khoei, H. Ould Slimane, and N. Kaabouch. Deep learning: Systematic review, models, challenges, and research directions. *Neural Computing and Applications*, 2023.
14. Pooja Chhabra and D. S. Goyal. A thorough review on deep learning neural network. In 2023 International Conference on Artificial Intelligence and Smart Communication (AISC), pages 220–226, 2023.