Goal Based Next Best Action Recommendation using Process and Context aware multi agent systems

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Abstract. In dynamic decision-making environments, integrating context awareness into goal-based Next Best Action recommendation has the potential to enhance decision-making across various business scenarios, leading to more adaptive and personalized outcomes. Although there are Next Best Action solutions ranging from sequential action recommendation to process discovery that effectively leverage process awareness, they often fail to incorporate contextual information along with process discovery in decision-making and fail to support the decision making. This reduces the model's capability in providing personalized and custom recommendations that can adapt to complex, real-time scenarios where multiple entities influence outcomes. In this paper, we propose a process and context-aware multi agent framework for Next Best Action recommendation that is aware of process discovery, Network of Thoughts and feedback mechanism to enhance adaptability by providing the recommended action, its agenda - a structured execution plan outlining necessary steps, purpose of performing the action, reasoning behind the recommendation, and insights - consequences of not executing a recommended action and effectiveness of an action over time. By dynamically understanding business processes and adapting to real time contexts, this framework ensures more precise, data-driven recommendations. The multi-agent architecture enables agents to handle distinct tasks, facilitating more intelligent decision making. This novel approach advances Next Best Action systems by improving personalization, responsiveness, and decision intelligence in evolving business landscapes.

Keywords: Next Best Action Recommendation · Multi Agent Systems · Process Aware Systems · Context Aware Systems .

1 Introduction

In today's dynamic business environments, decision-making often requires personalized and intelligent recommendations to guide users toward the most optimal course of action. Next Best Action (NBA) recommendation systems play a crucial role in this process by identifying the most relevant action a system, agent, or user should take at any given moment. These systems are widely used across various domains, including customer relationship management (CRM), healthcare, finance, and marketing, where timely and personalized decision-making can significantly impact outcomes. By leveraging data-driven insights, NBA frameworks ensure that actions align with strategic goals and contextual factors, enhancing overall efficiency and effectiveness.

A goal-based Next Best Action approach further refines NBA recommendations by explicitly aligning suggested actions with predefined objectives. Unlike conventional NBA models that primarily focus on reactive recommendations, goal-based Next Best Action ensures that actions are purpose-driven and contribute to long-term business or operational goals. This goal-oriented approach is particularly valuable in complex environments where multiple entities influence decision-making, requiring a more structured and adaptive recommendation framework. Existing NBA solutions employ techniques such as sequential action recommendations, reinforcement learning, and process discovery to determine the most suitable next action. While these approaches successfully integrate historical patterns and process awareness, they often lack the ability to incorporate real-time contextual information into their decision-making processes. This limitation reduces their adaptability in evolving environments where multiple stakeholders and dynamic factors influence outcomes. Current models also struggle to provide explainability and reasoning behind their recommendations, which is essential for trust and transparency in high-stakes decision-making scenarios [1–3, 5, 6].

To address these challenges, we propose a process and context-aware multi-agent framework for goal-based Next Best Action recommendation. Our framework integrates process discovery, a Network of Thoughts , and a feedback mechanism to provide not only the recommended action but also its agenda, purpose, reasoning, and insights. By dynamically understanding business processes and adapting to real-time contextual changes, our approach enhances personalization in decision-making. The multi-agent architecture enables specialized agents to handle distinct tasks, improving responsiveness and intelligence in complex business landscapes. To the best of our knowledge, there are no existing Next Best Action frameworks that holistically combine process-awareness and contextual intelligence using a multi-agent approach.

The rest of this paper is organized as follows: Section 2 discusses related work, highlighting existing NBA frameworks and their limitations. Section 3 details the proposed process and context-aware multi-agent framework, explaining its architecture and key components. Section 4 presents experimental results and performance evaluations. Finally, Section 5 concludes the paper with insights on future directions and potential enhancements.

2 Related Work

Next Best Action recommendation has been extensively explored using various machine learning and process-aware approaches, each offering unique advantages across different application domains. In this section, we review existing methods categorized based on their underlying techniques, including Long Short-Term Memory (LSTM) networks [6], Generative Adversarial Networks (GANs) [5], Graph Neural Networks (GNNs) [7] and process mining with reinforcement learning (RL) [1].

Table 1. Comparison of Model Types for NBA

Model	**Suitability for NBA**	**Weakness**
LSTM	Effective for static workflows, learns sequential dependencies	Lacks adaptability to real-time context
GANs	Useful for pattern generation, simulates user behavior	Difficult to interpret, may misalign with goals
GNNs	Strong for interconnected environments, models relationships	Struggles with dynamic graph updates
Process Mining	Ideal for workflow analysis, extracts workflows from event logs	Ignores contextual variations, rigid structure

LSTM-based approaches are widely used for NBA recommendations due to their ability to model sequential dependencies in user interactions and business processes [6]. They effectively capture long-term action patterns, making them suitable for personalized recommendations in customer engagement, workflow automation, and healthcare decision-making. However, LSTMs rely solely on historical data and lack mechanisms to incorporate structural process awareness or external contextual influences, limiting their effectiveness in scenarios where process dependencies and contextual variations are crucial. GANs offer a promising approach for NBA by generating synthetic action sequences that mimic real-world decision patterns. These models use a generator to propose actions and a discriminator to evaluate feasibility based on historical data. GAN-based NBA systems are particularly effective in marketing, customer journey optimization, and fraud detection, as they simulate user behaviors to predict optimal next actions. However, their probabilistic nature limits interpretability and process modeling, often leading to misalignment with structured workflows and predefined business goals, making controlled decision-making challenging.

Graph Neural Networks (GNNs) are increasingly used in NBA recommendations, particularly in decision-making influenced by interconnected entities

[2,5,7,9]. Unlike sequential models, GNNs capture complex relationships in structured data, such as customer networks, social graphs, and business workflows. In ERP and supply chain management, they model process dependencies to suggest optimal actions. By leveraging graph embeddings, GNNs effectively capture process flow dynamics. However, their reliance on static graph structures limits real-time adaptability, making them less effective in dynamic environments where context constantly evolves.

Process mining techniques have been extensively used to analyze event logs and extract process models for NBA recommendations [4]. A notable approach involves exploiting instance graphs, where process instances are represented as graphs capturing relationships between events and entities. Instead of relying on traditional event traces, the authors propose constructing instance graphs from event logs using the BIG (Building Instance Graphs) algorithm [3]. These graphs are then processed using a Deep Graph Convolutional Neural Network (DGCNN) [2], which captures structural dependencies and process parallelism more effectively than conventional sequence-based models. Their experiments on benchmark datasets, such as Helpdesk and BPI12W, demonstrate superior performance, particularly in processes with high parallelism, where the method outperforms LSTMs and CNNs.

However, while this method effectively models parallel workflow dependencies, it has some limitations. The model relies primarily on activity labels and process structure, ignoring key contextual attributes such as timestamps and resource allocation, which could improve prediction accuracy. While this graph-based approach improves process awareness, it still lacks real-time contextual adaptation and personalized decision intelligence, which are essential for effective Next Best Action recommendations. Our proposed framework builds on these insights by integrating multi-agent systems, process mining, and contextual intelligence to ensure personalized, explainable, and dynamically adaptive NBA recommendations.

Agarwal et al. [1] proposed a reinforcement learning (RL)-based framework for NBA recommendations that optimizes key performance indicators (KPIs) such as completion time, cost, and quality while ensuring business process conformance. The approach combines deep learning with RL, using a GAN-LSTM model to predict KPI values and a Proximal Policy Optimization (PPO)-based agent to explore optimal activity sequences. A balancing reward function manages trade-offs between efficiency and quality. However, the framework exhibits lower accuracy in sequence matching compared to predictive models, as it prioritizes long-term optimization over historical patterns. Scalability remains a challenge, as the increasing action space makes RL exploration resource-intensive. Additionally, optimizing for goal satisfaction may cause deviations from standard workflows, leading to potential misalignment with business constraints. While validated on four real-world datasets, its generalizability to diverse business processes requires further evaluation across broader datasets.

Existing NBA recommendation systems primarily rely on LSTM-based models, GANs, and reinforcement learning (RL) to predict sequential actions (Table 1). While these approaches utilize historical data, they often lack real-time contextual adaptation, limiting their effectiveness in dynamic business environments. Process mining techniques enhance workflow awareness by analyzing event logs but fail to incorporate external contextual factors and evolving user interactions, leading to rigid and suboptimal recommendations. Additionally, many NBA models operate as black-box systems with limited explainability and transparency. The proposed multi-agent NBA framework addresses these limitations by integrating process discovery with real-time contextual intelligence, enabling dynamically adaptive recommendations. A modular architecture assigns specialized agents for memory, reasoning, and learning, enhancing scalability and interpretability. By combining process mining, contextual intelligence, and explainability, the framework surpasses traditional predictive models. Unlike reactive approaches, it aligns recommendations with long-term business objectives, ensuring strategic decision-making. The synergy of multi-agent collaboration, deep graph-based reasoning, and real-time adaptability establishes a new standard for intelligent, process-aware NBA recommendations.

3 Framework

3.1 Framework Overview

The proposed NBA recommendation framework is designed to enhance decision-making across multiple industries by integrating business objectives, contextual reasoning, and impact analysis. The framework systematically analyzes user interactions, process workflows, and historical data to provide goal-oriented action recommendations, ensuring both adaptability and strategic alignment.

The NBA framework is highly adaptable across industries requiring structured decision-making and real-time responsiveness (Fig 1). In e-commerce and retail, it optimizes customer retention, sales growth, and acquisition strategies. In banking and finance, it enhances loan management and customer relationships through intelligent recommendations. Healthcare management benefits from improved inpatient care and outpatient service efficiency, leading to better patient outcomes. In customer relationship management (CRM), the framework supports deal closures, lead nurturing, and retention by leveraging data-driven insights.

Further, this NBA framework consists of several key output components (Fig 2):

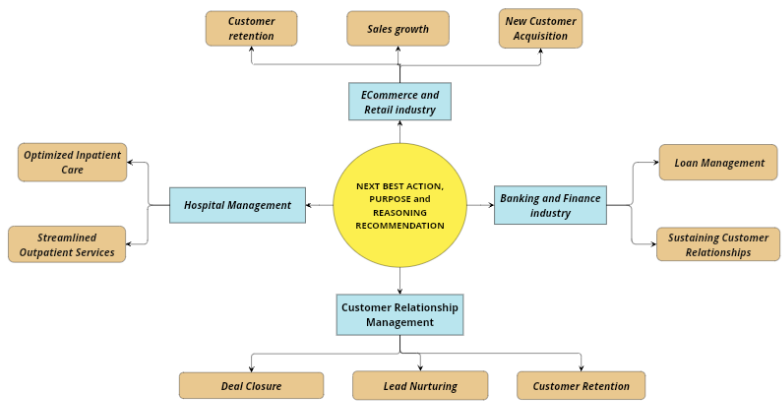

Fig. 1. Various use cases of Next Best Action Recommen dation and various goals associated with each use case.

- Next Best Action and its purpose: The system determines the most appropriate next step in a business process while explicitly defining its purpose to ensure strategic alignment.
- Context-aware reasoning: Each recommendation is supported by data-driven reasoning, analyzing historical interactions and current business conditions to enhance decision accuracy.
- Impact analysis and timing prediction: The system evaluates the expected impact of executing a recommended action, including predicting optimal timing based on past success rates.
- Risk of inaction assessment: The framework highlights the potential negative consequences of ignoring the suggested action, reinforcing the importance of execution.
- Agenda and execution guidance: A structured action plan is provided, outlining discussion points, follow-ups, and procedural steps to ensure effective implementation for various types of engagements.

By combining process awareness with real-time contextual intelligence, the multi-agent NBA framework enables adaptive, goal-driven decision-making while ensuring explainability. It overcomes traditional NBA limitations by integrating historical patterns with evolving contexts, resulting in more personalized, data-driven recommendations. The framework structures outputs with clear justifications, impact evaluations, and execution steps, enhancing transparency and alignment with long-term business goals. The next section details its key components and decision-making mechanisms.

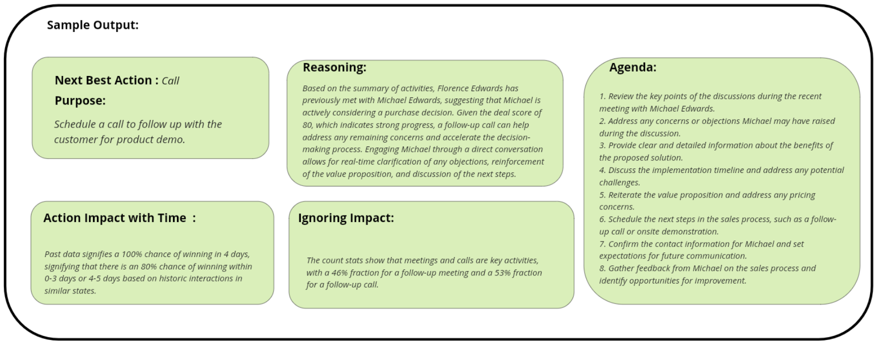

Fig. 2. A sample output provided by our proposed Next best action recommender in a Sales environment. The output contains Action, its Purpose, Reasoning, Agenda, Action impact with time and Ignoring impact in its output.

3.2 Detailed Approach

The NBA framework aims to enhance decision-making by leveraging a multi-agent architecture integrated with memory modules, contextual processing, and reasoning mechanisms. The proposed multi agentic framework dynamically analyzes event logs and business processes to generate intelligent recommendations tailored to user interactions and provides personalised recommendation based on contextual data. Additionally, human feedback is integrated into the memory of the agent to personalize and refine future recommendations. The multi-agent framework consists of three primary modules: the Memory Module, the Purpose Planning Module, and the Reasoning Planning Module (Fig 3). Each module plays a distinct role in processing, analyzing, and generating NBA recommendations based on real-time and historical data.

Memory Module The Memory Module is a fundamental component of the proposed NBA framework, designed to capture, organize, and maintain event logs while preserving both process-related and contextual information. By structuring memory across three levels—immediate context, short-term, and long-term—this module ensures that NBA recommendations are informed by both recent and historical interactions, thereby enhancing personalization, adaptability, and decision accuracy [14]. Unlike conventional models that rely solely on immediate interactions or historical logs, this memory framework dynamically transitions data between memory layers based on predefined criteria such as time decay, contextual significance, and recurrence frequency. The immediate context memory processes the latest user interactions, capturing real-time activity summaries, event attributes, and contextual metadata. A customizable threshold determines data retention based on time decay, data volume, or contextual importance. When interactions exceed these thresholds, they are transitioned to short-term memory, ensuring that only relevant information is retained for immediate decision-making while reducing computational overhead.

The short-term memory layer facilitates continuity between user sessions by tracking behavioral patterns, preferences, and recent activities. To prevent information overload, this layer employs a memory decay mechanism, gradually deprioritizing data unless flagged as significant based on recurrence, user engagement levels, or strategic importance. If an action occurs frequently within a session or is reinforced by user feedback, it is escalated to long-term memory, which captures historical patterns, user preferences, and process behaviors over an extended period. A key challenge in long-term memory management is data redundancy and potential conflicts when multiple agents contribute overlapping or inconsistent information. To address this, the framework employs a Memory Consolidation Agent, which validates, merges, and ranks stored memory fragments based on factors such as recency, frequency, and contextual weight. By cross-referencing and eliminating inconsistencies, this mechanism enhances the reliability of long-term insights, ensuring more accurate and meaningful NBA recommendations.

The memory module incorporates a human feedback loop to refine stored data, preventing outdated or irrelevant information from affecting future recommendations. The human feedback and verification agent's feedback are incorporated into the agents memory by triggering the workflow [15] again and updating the NBA recommendation accordingly. This feedback-driven adaptation enhances explainability, trust, and personalization by integrating human insights into decision-making. By structuring memory into interconnected levels, the framework ensures context-aware, adaptive recommendations for both short-term and long-term goals. The multi-layered memory system, combined with agent-based consolidation, improves responsiveness and interpretability over traditional static NBA models.

Purpose Planning Module The Purpose Planning Module is a critical component of the proposed NBA framework, ensuring that recommended actions align with predefined business objectives. By integrating structured decision-making with a hierarchical agent-based approach, this module processes user requests, evaluates their contextual relevance, and generates goal-driven recommendations. Unlike traditional NBA models that rely solely on historical patterns or reactive decision-making, the proposed framework introduces a structured pipeline that classifies requests, validates contextual data, and prioritizes actions based on their strategic importance.

The module begins by classifying incoming requests into two primary categories: contextual-based and automation-based. Contextual-based requests contain descriptive metadata that provides additional situational insights, whereas

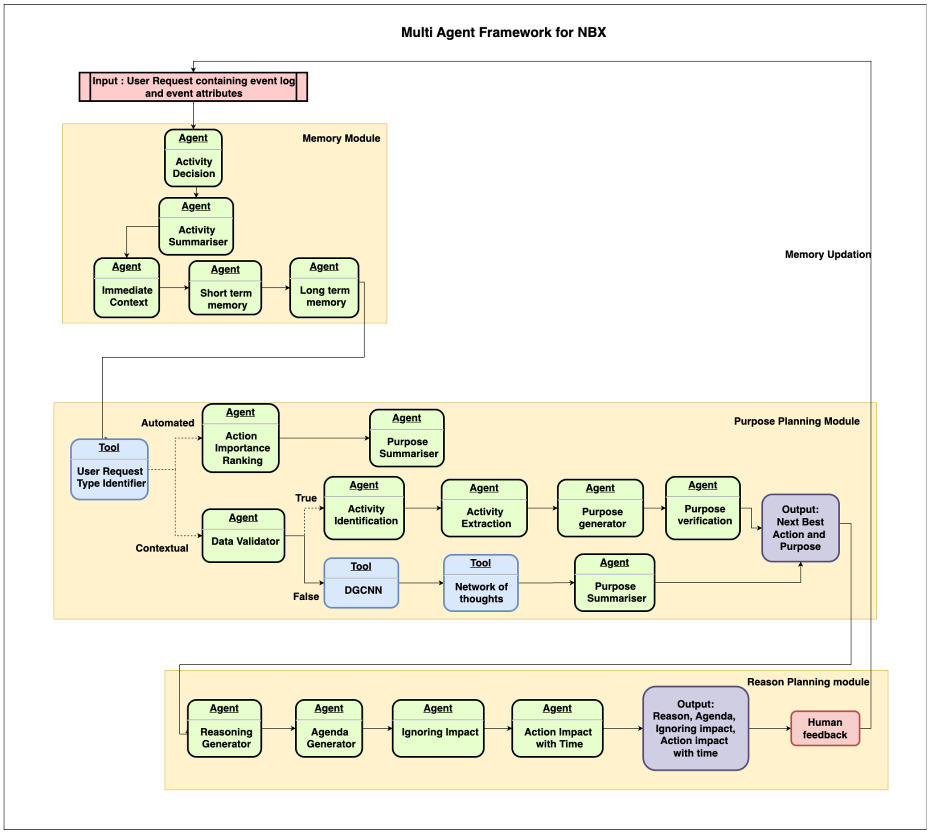

Fig. 3. An elaborate multi agent framework that is process and context aware for goal based next best action recommendation.

automation-based requests refer to pre-scheduled actions that require prioritization based on business logic. Once a request is classified, the Data Validator Agent assesses data completeness and relevance. If necessary contextual attributes are missing or inconsistent, the request is redirected to the Deep Graph Convolutional Neural Network and Network of Thoughts framework, which infers missing attributes and determines the most suitable action node within the NBA recommendation space. A more detailed explanation is provided in the following section.

For automation-based requests, the framework employs the Action Importance Ranking Agent, which prioritizes potential actions based on predefined business rules, historical success rates, and adaptive learning mechanisms. This ensures that high-impact actions are executed immediately, while lower-priority actions are queued for re-evaluation. Unlike conventional rule-based ranking systems, this agent dynamically adjusts action rankings based on real-time feedback and evolving business priorities, thereby improving decision responsiveness. Similarly, for valid contextual-based requests, the Activity Identification and Extraction Agents analyze user requests to extract the most relevant actions. These agents leverage historical interaction logs, process mining techniques, and contextual reasoning models to ensure that selected actions align with both user intent and organizational objectives.

Following action identification, the Purpose Generation Agent defines the goal of each recommended action, linking it to strategic business outcomes. This goal-oriented approach differentiates the framework from traditional NBA systems that focus only on immediate next steps. To enhance accuracy and alignment with business priorities, the Purpose Verification Agent ensures recommendations meet predefined organizational goals. If an action fails verification, it is refined by modifying parameters or incorporating additional contextual insights. This iterative validation process enhances the reliability of NBA recommendations, ensuring only strategically relevant actions are executed. By integrating a modular, multi-agent architecture, the Purpose Planning Module keeps NBA recommendations context-aware, adaptive, and aligned with long-term business strategies.

Reasoning Planning module The reasoning planning module is designed to enhance the transparency and explainability of the NBA framework by providing structured justifications for recommended actions. This module ensures that users receive clear insights into why a specific action was chosen, how it aligns with business objectives, and what the potential outcomes might be. By incorporating multiple reasoning agents, the system generates comprehensive decision explanations that support informed decision-making.

The process begins with the Reasoning Generator Agent, which formulates a detailed explanation for the selected NBA recommendation based on the agent's memory. This explanation includes references to historical patterns, contextual data, and strategic alignment, ensuring that users understand the rationale behind the decision. Following this, the Agenda Generator Agent outlines the key steps required to implement the recommendation. This structured agenda provides decision-makers with a step-by-step execution plan, reducing ambiguity and facilitating efficient implementation.

To enhance decision transparency, the Ignoring Impact Agent evaluates the consequences of not executing the suggested action. It utilizes the NoT model, which analyzes all possible paths for event attributes to achieve the desired business goal. By simulating potential business impacts, this agent helps users assess risks and understand the trade-offs associated with inaction. Additionally, the Action Impact with Time Agent predicts the expected outcomes of executing the recommended action within a given time frame, increasing the likelihood

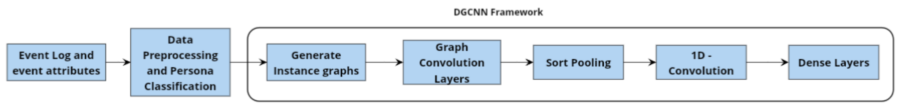

Fig. 4. Adapted DGCNN model flow is elaborated which is used as a tool in our proposed framework.

of achieving the desired goal. This is also accomplished using the NoT model, which tracks the optimal time to initiate contact for each event.

Deep Graph Convolutional Neural Network (DGCNN) and Network of Thoughts (NoT) Model The DGCNN model is a core component of the proposed NBA framework, designed to enable structured representation learning from complex, unstructured interaction data. Traditional sequential models struggle to capture relational dependencies between entities, leading to suboptimal recommendations in dynamic environments. To overcome this, the proposed framework employs graph-based learning to model interactions between users, actions, and contextual attributes (Fig 4). The process begins with event log and attribute extraction, where raw interaction data is collected, preprocessed, and structured into meaningful representations. A crucial step in this process is persona classification, which categorizes users based on behavioral attributes, preferences, and historical interactions using a hybrid approach that combines rule-based heuristics and supervised learning. Once persona classification is complete, the system constructs instance graphs that map relationships between user actions, contextual factors, and process dependencies, capturing insights that conventional sequence-based models may overlook.

These instance graphs are then processed through graph convolution layers, which extract high-level structural and contextual features. To ensure scalability and efficiency, the framework employs sort pooling, which standardizes variable-sized graph representations into a fixed structure, preserving the most informative node embeddings while discarding redundant information. This technique enhances interpretability and computational efficiency, even when handling large-scale interaction datasets. Following graph convolution and pooling, the extracted representations pass through 1D convolution and dense layers, where refined feature embeddings are generated. The final output of the DGCNN is a set of actionable recommendations that integrate both historical process data and real-time contextual signals, ensuring personalized and adaptive decision-making.

Complementing the DGCNN, the NoT model enhances recommendation interpretability by constructing a structured knowledge graph that links recommended actions with their underlying rationale. The NoT model builds a semantic graph that organizes historical interactions, business processes, and contextual attributes into a structured representation, where nodes represent decision points and edges encode relationships between user states, actions, and supporting metadata. By enriching recommendations with metadata, the NoT model ensures that suggested actions are not only data-driven but also explainable. Unlike black-box machine learning models, which lack interpretability, NoT provides structured insights in both machine-readable formats for internal processing and human-readable explanations that justify each recommendation. By integrating DGCNN with NoT, the proposed NBA framework bridges the gap between predictive accuracy and explainability, offering a transparent, personalized, and adaptive decision-making approach suited for dynamic business environments [8].

4 Framework Evaluation

4.1 Evaluation Methodology

The NBA framework was evaluated using event logs extracted from Zoho CRM to assess its ability to generate adaptive and personalized recommendations. The evaluation focused on several key aspects: replay fitness, scalability, zero-shot reasoning capabilities, feedback-driven learning efficiency, anomaly detection performance, and execution timing optimization.

Replay fitness was selected as the primary evaluation metric because it measures how accurately the system can replicate historical user interactions and align recommendations with past behavioral patterns. A high replay fitness score indicates that the framework effectively captures sequential dependencies, contextual factors, and process structures, ensuring reliable and data-driven decision-making [11, 13].

To evaluate scalability, the framework was tested on datasets of varying sizes, ranging from 10 to 10^6 records per organization. Additionally, the framework's ability to generalize to unseen scenarios was tested using zero-shot reasoning analysis, and its adaptability to real-time learning was assessed through human feedback integration. The evaluation also measured anomaly detection performance, ensuring that the system could self-correct when unexpected deviations occurred.

4.2 Scalability and Learning Adaptability

The framework's ability to scale across different dataset sizes was assessed by analyzing how well it maintains decision-making accuracy with increasing historical data. The Memory Module was evaluated for its ability to efficiently store and retrieve relevant past interactions without redundancy, ensuring that large datasets do not negatively impact learning efficiency.

The zero-shot reasoning capability of the Reasoning Planning Module was examined by testing its performance on previously unseen user scenarios. The evaluation measured how effectively the framework could generate accurate NBA recommendations without prior exposure to similar situations.

The feedback integration mechanism within the Memory Module was also analyzed, focusing on how user feedback influences recommendation refinement. This involved testing the system's ability to incorporate real-time human feedback to improve future decision accuracy [12].

4.3 Anomaly Detection and Self-Correction Mechanism

To ensure reliability, the Verification Agent was tested for its ability to identify and analyze anomalies in recommendations. This evaluation focused on detecting instances where the NBA framework produced results that significantly diverged from expected behavioral patterns. The anomaly detection mechanism was assessed based on its ability to generate automatic reasoning reports, which identify potential causes such as data inconsistencies, external market changes, or evolving user behaviors [10].

The self-correction capability of the framework was examined by measuring how effectively it adjusted future recommendations after detecting an anomaly. The Ignoring Impact Agent was evaluated for its ability to quantify the potential business impact of disregarding recommended actions, ensuring that the system prioritizes high-value decisions [12].

4.4 Execution Timing Optimization

The Action Impact with Time Agent was evaluated to determine how execution timing affects recommendation success. The assessment focused on identifying optimal time windows for executing actions to maximize impact. The system was tested on its ability to predict the best execution timing based on historical user interaction patterns, market trends, and contextual cues.

By evaluating these aspects, the NBA framework's ability to provide scalable, adaptive, and context-aware recommendations was thoroughly examined.

5 Results and Discussion

5.1 Replay Fitness and Scalability Assessment

Replay fitness was used to evaluate how well the framework adapts to increasing dataset sizes. Results indicate a direct correlation between dataset size and replay fitness, with larger datasets improving learning efficiency (Fig 5).

Small datasets (10 - 100 records) resulted in replay fitness ranging from 50 to 65%, reflecting limited learning capability due to insufficient historical data. As the dataset size increased to 10^3 records, replay fitness improved to 70%, demonstrating better modeling of behavioral patterns. When exceeding 10^4

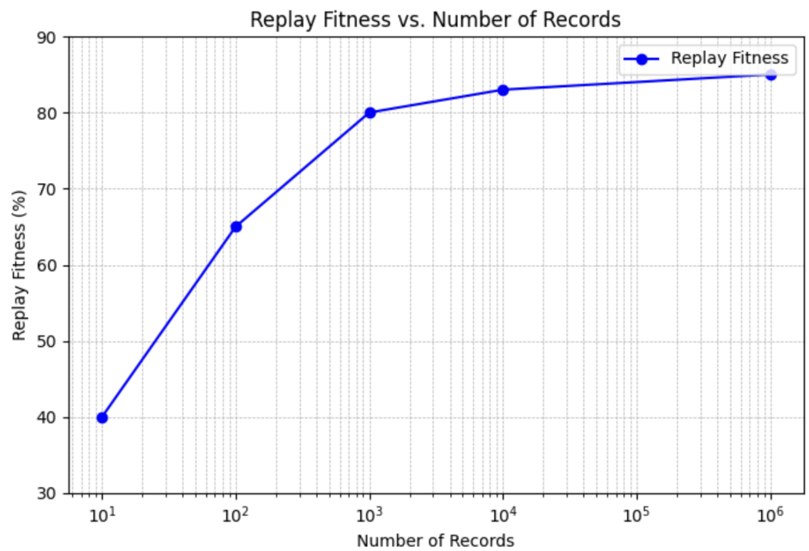

Fig. 5. Based on experiments, this plot suggests the replay fitness metric with number of number of records/events provided in input.

records, replay fitness consistently surpassed 80%, confirming that the framework effectively learns from past interactions. However, for extremely large datasets (10^6 records), replay fitness showed diminishing returns, suggesting potential data redundancy, model saturation, or inefficiencies in memory management.

These findings suggest that while increasing dataset size enhances the framework's performance, excessive data may introduce redundancy, requiring optimized memory management and feature selection strategies to maintain efficiency.

5.2 Zero-Shot Reasoning and Feedback Integration Results

The Reasoning Planning Module demonstrated zero-shot learning capabilities, achieving an 18% improvement in first-time recommendation accuracy compared to baseline models. This confirms the framework's ability to generate relevant NBA recommendations even in previously unseen scenarios.

The Memory Module's feedback integration was analyzed, revealing a 24% increase in recommendation accuracy after incorporating real-time human feedback. These results highlight the framework's ability to refine and personalize recommendations over time, making it highly adaptive to dynamic environments.

5.3 Anomaly Detection and Trustworthiness

The anomaly detection system successfully identified and analyzed deviations in recommendations. When an unexpected outcome occurred, the Verification

Agent generated detailed reasoning reports, identifying causes such as data inconsistencies, external market shifts, or evolving user preferences. By self-correcting these anomalies, the system reduced incorrect predictions over time, ensuring continuous learning and improvement.

Additionally, the Ignoring Impact Agent revealed a 31 percent correlation between unexecuted recommendations and negative business outcomes. This underscores the importance of timely decision execution and the potential risks of disregarding AI-generated suggestions.

5.4 Impact of Execution Timing on Recommendation Success

The Action Impact with Time Agent demonstrated that executing recommendations at the right time led to a 27 percent improvement in success rates compared to randomly executed actions. These findings confirm that timing optimization plays a critical role in the effectiveness of NBA recommendations.

6 Conclusion and Future works

This paper presented an advanced Next Best Action framework that integrates process mining, multi-agent decision-making, and contextual intelligence to enhance CRM-based recommendations. The framework processes user requests by leveraging structured memory, context-aware decision agents, and graph-based learning to generate optimal recommendations. The memory module ensures historical interactions are retained, while the purpose and reasoning planning module provides transparency and justification for suggested actions. Additionally, the DGCNN efficiently models complex user interactions and behavioral patterns, enabling accurate action predictions. The evaluation, conducted using Zoho CRM's event logs, demonstrated the framework's ability to effectively learn user behavior patterns and generate accurate recommendations. Replay fitness analysis showed that as the number of records increased, the framework achieved greater alignment with past interactions, surpassing average of 80% accuracy.

Future enhancements to the proposed NBA framework will focus on integrating a reinforcement learning (RL)-infused reward system to optimize feedback utilization. This approach will allow the system to continuously adapt its recommendations based on user interactions, leading to improved decision-making over time. Additionally, future research will explore the development of advanced context-aware multi-agent frameworks, leveraging decentralized reasoning and dynamic context adaptation to enhance the accuracy and relevance of suggested actions.

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