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A Foundational Framework for Intelligent Data-Driven Decision Support Systems Based on Adaptive Preference Learning

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Abstract

The increasing complexity of organizational decision-making, driven by heterogeneous data, evolving user preferences, and dynamic business environments, has exposed the limitations of conventional Decision Support Systems (DSS). Traditional DSS rely on static decision models and predefined preferences, limiting their adaptability and personalization. Although Artificial Intelligence (AI)-based DSS have improved predictive capabilities, many still lack adaptive preference learning, continuous feedback, explainability, and lifelong learning. This study aims to develop a Foundational Framework for Intelligent Data-Driven Decision Support Systems (ID-DSS) based on Adaptive Preference Learning (APL). The research adopts the Design Science Research (DSR) methodology, incorporating a systematic literature review, problem identification, requirement analysis, framework design, and conceptual validation. The proposed framework integrates data analytics, adaptive preference learning, decision intelligence, explainable AI, continuous feedback, and knowledge updating within a closed-loop learning architecture. The Adaptive Preference Learning mechanism continuously refines user preferences using explicit feedback, implicit behavioral observations, contextual information, and incremental learning, enabling recommendations to become increasingly personalized and adaptive. Furthermore, explainable AI enhances transparency by providing interpretable reasoning for recommendation outcomes. The proposed framework establishes a theoretical foundation for next-generation intelligent DSS that are adaptive, personalized, transparent, context-aware, and capable of continuous learning, with potential applications across healthcare, finance, manufacturing, education, smart cities, and public administration.

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1. Introduction

The rapid advancement of digital technologies has fundamentally transformed organizational decision-making processes across various sectors. Organizations now operate in increasingly dynamic environments characterized by massive volumes of heterogeneous data, rapidly changing market conditions, evolving user behaviors, and growing uncertainty[1]. Emerging technologies such as

Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), cloud computing, and big data analytics have significantly expanded the availability of real-time information for supporting strategic, tactical, and operational decisions. As a result, organizations require Decision Support Systems (DSS) that not only process large-scale data but also adapt to changing environments and provide personalized recommendations that improve decision quality. Consequently, the role of DSS has evolved from static analytical tools toward intelligent systems capable of continuous learning and adaptive decision support.

Since their emergence in the 1960s and 1970s, Decision Support Systems have evolved considerably. Early DSS primarily relied on rule-based reasoning, structured databases, and mathematical models to assist managers in solving semi-structured decision problems. These systems proved effective in relatively stable environments but generally assumed that user preferences and decision criteria remained constant over time. Decision rules and model parameters were predefined during system development and rarely updated after deployment. While suitable for predictable business settings, such assumptions limit the capability of traditional DSS to respond to dynamic organizational environments where user priorities and contextual conditions continuously change.

The emergence of big data has dramatically reshaped the decision-making landscape. Organizations continuously generate structured and unstructured data through enterprise systems, social media, IoT devices, digital transactions, and customer interactions[2]. These data contain valuable information regarding user behavior, operational performance, market dynamics, and contextual changes. Simultaneously, advances in AI and ML have enabled organizations to identify hidden patterns, predict future events, and automate complex decision-making processes with unprecedented accuracy. AI-driven DSS have therefore become increasingly important across various domains, including healthcare, finance, education, manufacturing, logistics, and public administration. Nevertheless, although predictive capabilities have improved substantially, the availability of large-scale data alone does not necessarily guarantee better decisions because effective decision-making also depends on understanding evolving human preferences.

Recent research has increasingly emphasized adaptive preference learning as a key component of intelligent decision support. Wirth, Akrour, Neumann, and Fürnkranz (2017) demonstrated that intelligent systems can learn user preferences directly from behavioral observations and comparative feedback instead of relying solely on predefined utility functions. Their work established preference learning as an effective alternative for environments where explicit preference information is unavailable. Similarly, research on human-centered and explainable AI has shown that user feedback should become an integral component of continuous learning systems, allowing intelligent recommendations to evolve according to changing user needs and decision contexts. More recently, Dycke, Simpson, Kuznetsov, and Gurevych (2021) successfully applied preference learning to scholarly peer-review decision support, illustrating that adaptive preference modeling can improve decision quality in complex multi-criteria environments.

The integration of Preference Learning (PL) with Multiple Criteria Decision Aiding (MCDA) has further expanded the theoretical foundation of adaptive decision support. Hüllermeier and Słowiński (2024) argued that combining machine learning-based preference modeling with multi-criteria decision analysis creates new opportunities for developing transparent, adaptive, and explainable decision support systems. Likewise, Meng, Lin, Wu, and colleagues (2024) proposed an adaptive Graph Neural Network framework that combines preference learning with TOPSIS-based decision analysis, demonstrating improved recommendation accuracy while maintaining model interpretability. These studies indicate that adaptive preference learning has become an increasingly important research direction for next-generation intelligent DSS.

Despite these significant advances, several important challenges remain. Decision makers rarely maintain fixed preferences because organizational objectives, environmental conditions, accumulated experience, and contextual information continuously evolve[3]. Consequently, effective decision support systems should be capable of continuously updating user preference models rather than relying on predefined decision criteria. Personalized recommendations have therefore become essential because different users frequently require different decision alternatives even when analyzing the same dataset. Intelligent DSS must therefore incorporate mechanisms that continuously learn from user interactions and behavioral feedback to ensure recommendations remain relevant over time.

However, most existing DSS continue to treat user preferences as static variables. Decision models are often manually configured and require extensive human intervention whenever organizational priorities change[4]. Although AI-based decision support systems have substantially improved predictive performance through advanced analytics and machine learning, many primarily focus on prediction accuracy rather than adaptive preference learning. As a result, these systems frequently fail to capture how user priorities evolve during continuous interactions, leading to recommendations that gradually lose relevance in dynamic decision environments.

Another important limitation concerns the fragmented nature of current intelligent decision support research. Existing studies commonly focus on individual technologies such as predictive analytics, recommender systems, explainable AI, reinforcement learning, or preference modeling independently[5]. Only a limited number of studies integrate these capabilities into a unified framework capable of simultaneously performing data-driven analytics, adaptive preference learning, intelligent recommendation generation, continuous feedback processing, and explainable decision support. Furthermore, many AI-based recommendation systems still operate as black boxes, reducing transparency and limiting user trust. These shortcomings reveal a significant research gap in the development of comprehensive intelligent DSS architectures capable of continuously adapting to changing user preferences while maintaining explainability and personalization.

To address these limitations, this study proposes a foundational framework for Intelligent Data-Driven Decision Support Systems based on Adaptive Preference Learning. The proposed framework integrates data analytics, adaptive preference modeling, continuous learning mechanisms, intelligent recommendation generation, and explainable AI into a unified conceptual architecture[6]. Through continuous user feedback and iterative learning, the framework dynamically updates user preference models, enabling recommendations to remain personalized, transparent, and responsive to changing decision contexts. The framework is expected to improve decision quality, personalization, adaptability, and user trust while providing a theoretical foundation for future intelligent decision support systems capable of lifelong learning.

2. Research Methodolgy

This study employs Design Science Research (DSR) as the primary methodology to develop a foundational framework for Intelligent Data-Driven Decision Support Systems (ID-DSS) based on Adaptive Preference Learning (APL). DSR is widely recognized in Information Systems research as an appropriate methodology for developing innovative artifacts, including conceptual frameworks, architectures, models, algorithms, and software systems[7]. Unlike explanatory research that focuses on understanding existing phenomena, DSR emphasizes designing, developing, evaluating, and refining artifacts that solve practical problems while advancing scientific knowledge. Since this study aims to propose a novel framework integrating adaptive preference learning, intelligent decision support, and data-driven analytics, DSR provides a systematic and rigorous methodological foundation.

The research consists of seven sequential stages: Research Design, Systematic Literature Review, Problem Identification, Requirement Analysis, Framework Design, Adaptive Preference Learning Mechanism Development, and Framework Validation. These stages ensure that the proposed framework is theoretically grounded, methodologically rigorous, and practically applicable.

The first stage is Research Design, which follows the Design Science Research process proposed by Peffers et al. (2007). The process begins by identifying limitations in conventional Decision Support Systems and existing AI-driven decision support technologies, including static user preferences, limited adaptability, insufficient personalization, and the absence of continuous learning mechanisms. Based on these identified problems, the study defines research objectives and develops a conceptual framework that integrates adaptive preference learning, intelligent analytics, and explainable decision support. The framework is iteratively refined throughout the research process, allowing improvements based on theoretical analysis and expert feedback. The use of DSR is appropriate because the study focuses on constructing a novel conceptual artifact rather than testing causal relationships or explaining existing phenomena.

The second stage involves conducting a Systematic Literature Review (SLR) to establish the theoretical foundation of the proposed framework[8]. The review follows a structured process consisting of planning, literature identification, screening, eligibility assessment, quality evaluation, data extraction, synthesis, and reporting. Relevant publications are collected from major scientific databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect, and Google Scholar. The review primarily considers peer-reviewed publications published between 2016 and 2025. Literature searches employ keywords related to Decision Support Systems, Artificial Intelligence, Machine Learning, Adaptive Preference Learning, Recommender Systems, Human-Centered AI, Explainable Artificial Intelligence, Adaptive Systems, Multi-Criteria Decision Making, and Data Analytics. The selected studies are analyzed to identify existing methodologies, architectural components, adaptive learning strategies, preference modeling techniques, recommendation mechanisms, explainability approaches, and current research gaps. These findings provide the theoretical basis for constructing the proposed framework.

The third stage is Problem Identification, which systematically analyzes the shortcomings of existing intelligent decision support technologies. Conventional Decision Support Systems generally assume that user preferences remain static throughout the decision-making process, making them unsuitable for dynamic environments where organizational priorities and user requirements continuously evolve[9]. Existing recommender systems primarily focus on improving prediction accuracy using historical interactions but often fail to capture changing user preferences and contextual variations over time. Similarly, preference learning research tends to concentrate on isolated algorithms without integrating contextual adaptation, continuous feedback, explainability, and uncertainty management into a unified architecture. Furthermore, many AI-based decision support systems function as black-box models, limiting transparency, interpretability, and user trust despite their high predictive performance. These limitations highlight the need for a comprehensive framework capable of integrating adaptive preference learning, data-driven analytics, explainable AI, and continuous learning.

The fourth stage conducts a comprehensive Requirement Analysis to identify the functional and non-functional requirements of the proposed framework. Functional requirements include the ability to process heterogeneous data from multiple sources in real time, continuously update user preference models using explicit and implicit feedback, generate personalized recommendations through predictive analytics and multi-criteria decision analysis, collect continuous user feedback, and support context-aware decision-making by considering temporal, environmental, organizational, and user-specific factors. In addition to these operational capabilities, several non-functional requirements are identified. The framework should provide explainability through interpretable recommendation processes, ensure transparency regarding model evolution and preference updates, maintain scalability when processing increasing data volumes, protect user privacy throughout data processing, demonstrate robustness under uncertain and noisy environments, and guarantee fairness by minimizing bias in recommendation generation. These requirements guide the design of the proposed intelligent decision support architecture.

Based on these requirements, the fifth stage develops the Framework Design, which represents the primary artifact of this research. The proposed architecture consists of eleven interconnected modules that collectively establish a continuous intelligent decision-making cycle[10]. The process begins with the Data Layer, which collects structured and unstructured data from enterprise systems, IoT devices, online platforms, and external repositories. The Data Processing Layer performs data cleaning, normalization, transformation, and integration to ensure data quality. The processed data are forwarded to the Feature Engineering Module, where relevant behavioral, contextual, and decision-related features are extracted. These features are analyzed within the Preference Learning Module to construct personalized user preference models based on historical decisions, explicit ratings, implicit interactions, and contextual information. The Adaptive Learning Engine continuously refines these models through incremental learning techniques, enabling preference adaptation without complete model retraining. Updated preference models are utilized by the Decision Intelligence Engine, which integrates predictive analytics, optimization methods, and multi-criteria decision analysis to evaluate decision alternatives[11]. The resulting recommendations are generated by the Recommendation Generator and accompanied by transparent explanations produced by the Explanation Module, including feature importance and reasoning processes. User interactions are subsequently collected through the Feedback Collection Module, while the Knowledge Update Module incorporates new information into organizational knowledge repositories and preference models. Finally, the Continuous Learning Module closes the feedback loop by continuously updating learning models, allowing the framework to evolve alongside changing user behaviors and decision environments.

The sixth stage develops the Adaptive Preference Learning Mechanism, which constitutes the principal novelty of the proposed framework. The learning process begins with Preference Initialization, where initial preference profiles are established using demographic information, historical decision records, organizational roles, or explicitly specified preferences[12]. The framework then continuously performs Behavior Observation by monitoring user interactions, browsing behavior, decision selections, and contextual conditions. User preferences are inferred from both implicit feedback, such as click behavior, navigation patterns, interaction frequency, and recommendation acceptance, and explicit feedback, including ratings, rankings, questionnaires, and pairwise comparisons. These inputs are processed through a Preference Updating mechanism that dynamically adjusts preference weights whenever significant behavioral changes occur. Instead of rebuilding the model after each interaction, the framework employs Incremental Learning techniques that integrate new observations while preserving previously acquired knowledge. The learning process also incorporates Context Adaptation, enabling preference models to evolve according to environmental conditions, organizational priorities, temporal changes, and user contexts. In addition, the framework supports Online Learning, allowing real-time model updates as new interactions occur. Optional enhancements include Reinforcement Learning for optimizing recommendation policies through cumulative rewards, Bayesian Updating for managing uncertainty during preference estimation, and Preference Embeddings for representing complex preference relationships within latent feature spaces. Collectively, these mechanisms enable continuous adaptation, lifelong personalization, and improved recommendation quality.

The final stage is Framework Validation, which evaluates the completeness, consistency, novelty, and practical applicability of the proposed framework. Validation is conducted through several complementary approaches. Expert evaluation involves information systems researchers, artificial intelligence experts, and industry practitioners who assess the framework's architecture, theoretical contribution, and implementation feasibility. The Delphi Method may be employed to achieve consensus among multidisciplinary experts regarding framework components and adaptive learning mechanisms. Scenario-based validation examines framework performance under representative decision-making situations involving changing user preferences and dynamic environments. A prototype implementation may be developed to verify interactions among framework components and demonstrate practical feasibility[13]. Furthermore, case studies across multiple domains, such as healthcare, finance, education, manufacturing, and smart governance, may be conducted to evaluate adaptability in different organizational contexts. Simulation experiments can assess recommendation accuracy, computational efficiency, adaptability, preference convergence, and continuous learning performance using benchmark datasets. Finally, comparative analysis compares the proposed framework with conventional Decision Support Systems and existing AI-based decision support architectures based on adaptability, personalization, explainability, transparency, scalability, continuous learning capability, and recommendation quality. These complementary validation methods provide comprehensive evidence regarding the theoretical robustness and practical applicability of the proposed framework, establishing a strong foundation for future implementation and empirical evaluation.

3. Results and Discussion

3.1 Framework Overview

The primary outcome of this study is the development of a Foundational Framework for Intelligent Data-Driven Decision Support Systems (ID-DSS) Based on Adaptive Preference Learning (APL). The proposed framework addresses the limitations of conventional Decision Support Systems by integrating data-driven analytics, adaptive preference learning, explainable artificial intelligence (XAI), and continuous feedback into a unified architecture[14]. Unlike traditional DSS, which rely on static decision models and predefined user preferences, the proposed framework continuously learns from user interactions, adapts to changing decision contexts, and produces personalized recommendations that evolve over time. Consequently, the framework provides a conceptual foundation for next-generation intelligent decision support systems capable of operating effectively in dynamic, data-intensive environments.

The proposed architecture consists of eleven interconnected modules that form a continuous decision-making and learning ecosystem. These modules include the Data Layer, Data Processing Layer, Feature Engineering Module, Preference Learning Module, Adaptive Learning Engine, Decision Intelligence Engine, Recommendation Generator, Explanation Module, Feedback Collection Module, Knowledge Update Module, and Continuous Learning Module. Rather than functioning independently, these components interact continuously to exchange information, update knowledge, and improve recommendation quality through iterative learning.

The framework begins with the Data Layer, which collects structured and unstructured information from multiple internal and external sources, including enterprise databases, IoT devices, transactional systems, online platforms, and user interactions. Because raw data often contain inconsistencies, missing values, and noise, they are processed within the Data Processing Layer, where cleaning, normalization, integration, and transformation are performed to ensure high-quality datasets suitable for intelligent analysis.

The processed data are then forwarded to the Feature Engineering Module, which extracts meaningful behavioral, contextual, temporal, and decision-related features[15]. These engineered features provide concise representations of users and decision environments, serving as the primary input for adaptive preference modeling. The Preference Learning Module subsequently constructs personalized user preference models by analyzing historical decisions, explicit ratings, implicit interactions, and contextual information. Unlike conventional systems that assume fixed preferences, this module continuously updates preference representations as user behavior evolves.

The adaptive preference models are refined by the Adaptive Learning Engine, which employs incremental and online learning techniques to incorporate newly observed interactions without requiring complete model retraining. This capability enables the framework to maintain recommendation relevance even under rapidly changing user needs and organizational conditions. Updated preference models are then processed by the Decision Intelligence Engine, which combines predictive analytics, optimization methods, and multi-criteria decision-making techniques to evaluate available alternatives and identify the most appropriate recommendations.

The resulting recommendations are generated by the Recommendation Generator and presented together with transparent explanations produced by the Explanation Module. These explanations describe the reasoning behind each recommendation, including influential features, confidence levels, and preference contributions, thereby improving interpretability, transparency, and user trust. Following recommendation delivery, the Feedback Collection Module gathers both explicit feedback, such as ratings and evaluations, and implicit feedback, including click behavior, browsing patterns, interaction frequency, and recommendation acceptance. These observations are incorporated into the Knowledge Update Module, where organizational knowledge and user preference models are continuously refined. Finally, the Continuous Learning Module closes the learning cycle by updating all analytical models, enabling the framework to evolve continuously alongside changing user behaviors and environmental conditions.

The operational workflow follows a structured sequence that transforms raw organizational data into intelligent recommendations[16]. Data are first acquired from multiple heterogeneous sources and processed to ensure consistency and quality. Feature engineering then extracts meaningful information that accurately represents user behavior and contextual conditions. These features are analyzed by the Preference Learning Module to construct personalized preference models, which are subsequently refined through adaptive learning. The Decision Intelligence Engine evaluates decision alternatives using predictive analytics and multi-criteria decision analysis before the Recommendation Generator produces personalized recommendations. The Explanation Module provides interpretable justifications, while user feedback is continuously incorporated into the learning process to improve future recommendations.

The effectiveness of the framework depends on continuous interaction among all architectural components. Information flows sequentially from data acquisition to recommendation generation while simultaneously returning through the feedback mechanism to refine preference models and organizational knowledge. The Data Layer supplies updated information to downstream modules, the Preference Learning Module continuously adjusts user preference representations, and the Adaptive Learning Engine ensures that decision models remain aligned with evolving behavioral patterns. Similarly, feedback collected after recommendation delivery is incorporated into the Knowledge Update Module and subsequently utilized during future recommendation cycles. This bidirectional interaction enables continuous adaptation rather than one-time decision generation.

The proposed framework also establishes an integrated data flow and decision flow. The data flow begins with heterogeneous data collection, followed by preprocessing, feature extraction, adaptive preference modeling, decision analysis, recommendation generation, explanation, and feedback integration[17]. Meanwhile, the decision flow starts with problem identification and contextual analysis before combining learned preferences with predictive analytics and multi-criteria evaluation to rank decision alternatives. Because preference models are continuously updated, recommendations remain dynamic and responsive to changing user objectives rather than relying on static decision rules.

3.2 Component Description

The proposed Intelligent Data-Driven Decision Support System (ID-DSS) consists of six interconnected functional modules that collectively establish an adaptive and continuously learning decision support ecosystem. Rather than operating independently, each module exchanges information with the others to ensure that recommendations remain personalized, accurate, transparent, and responsive to changing user preferences and organizational environments.

The process begins with the Data Acquisition Layer, which serves as the primary gateway for collecting heterogeneous data from multiple sources[18]. These sources include enterprise databases, transactional systems, Internet of Things (IoT) devices, user profiles, behavioral logs, and contextual information such as time, location, and environmental conditions. By integrating both structured and unstructured data, this module provides a comprehensive representation of users, organizational activities, and decision contexts. Continuous data collection ensures that the framework always operates using the most recent information available.

The collected data are subsequently processed within the Data Analytics Engine, which transforms raw information into meaningful knowledge for intelligent decision-making. This module performs essential preprocessing activities, including data cleaning, normalization, integration, and feature extraction to improve data quality and consistency. It further applies predictive analytics and machine learning techniques to identify hidden patterns, classify decision situations, forecast future outcomes, and generate analytical insights. The resulting features provide a reliable foundation for adaptive preference modeling and intelligent decision analysis.

The extracted features are then analyzed by the Preference Learning Engine, which represents one of the key innovations of the proposed framework. This module constructs personalized preference models by combining historical decision records, user characteristics, contextual information, explicit feedback such as ratings, and implicit behavioral data including browsing history and interaction patterns. Unlike conventional Decision Support Systems that assume fixed user preferences, the Preference Learning Engine continuously learns changing priorities, decision tendencies, and behavioral evolution. Consequently, recommendation generation becomes increasingly personalized and remains aligned with evolving user needs.

The continuously updated preference models are managed by the Adaptive Learning Engine, which enables lifelong learning within the framework[19]. Instead of rebuilding models whenever new information becomes available, this module employs incremental and online learning techniques to efficiently incorporate newly observed interactions while preserving previously acquired knowledge. The Adaptive Learning Engine continuously updates preference weights, adjusts decision models, refines recommendation strategies, and adapts to changing contextual conditions. This capability allows the framework to respond effectively to dynamic environments while maintaining computational efficiency and model stability.

The refined preference information is subsequently processed by the Decision Intelligence Engine, which functions as the analytical core of the framework. This module integrates adaptive preference models with predictive analytics, optimization algorithms, and multi-criteria decision-making techniques to evaluate available alternatives. Based on comprehensive analysis of user preferences, contextual variables, organizational objectives, and decision constraints, the engine generates prioritized rankings, personalized recommendations, and alternative solutions. In addition, it performs risk analysis to estimate the uncertainty associated with each decision alternative, enabling decision-makers to make more informed and reliable choices.

To improve transparency and user trust, recommendation outcomes are interpreted by the Explanation Engine. Rather than presenting recommendations as black-box outputs, this module provides understandable explanations describing why a particular recommendation is generated[20]. It identifies influential features, explains the reasoning process behind recommendation rankings, illustrates the contribution of user preferences, and provides confidence scores that indicate the reliability of each recommendation. These explanations improve interpretability, strengthen user confidence, and encourage greater acceptance of AI-assisted decision support.

Collectively, these six modules establish a closed-loop intelligent decision support ecosystem in which data acquisition, analytical processing, adaptive preference learning, intelligent decision analysis, recommendation generation, and explainable artificial intelligence operate as an integrated system. Information continuously flows across modules through iterative feedback, allowing the framework to learn from every interaction, refine organizational knowledge, improve recommendation quality, and adapt to evolving decision environments. By integrating continuous learning, adaptive preference modeling, personalized recommendations, and transparent explanations, the proposed architecture overcomes the limitations of conventional Decision Support Systems and provides a robust conceptual foundation for future intelligent, data-driven decision support applications.

3.3 Decision Process

The proposed Intelligent Data-Driven Decision Support System (ID-DSS) follows a continuous and adaptive decision-making process that transforms raw organizational data into personalized and explainable recommendations through successive analytical and learning stages. The process begins with the input stage, where heterogeneous data are collected from multiple internal and external sources. These inputs include transactional records, enterprise databases, Internet of Things (IoT) sensors, user profiles, historical decision records, behavioral logs, contextual information, and environmental variables. The objective of this stage is to establish a comprehensive representation of both users and decision environments. Because decision quality depends heavily on data quality, the collected information is first standardized and prepared for subsequent analytical processing.

The second stage is analytics, where raw data are transformed into meaningful knowledge through data preprocessing and intelligent analysis[21]. This stage performs data cleaning, normalization, integration, feature extraction, and predictive analytics to identify significant behavioral patterns, contextual characteristics, and relationships among decision variables. Machine learning algorithms and data mining techniques further generate predictive insights that support more accurate decision-making. The analytical outputs provide structured knowledge that serves as the foundation for understanding user behavior and organizational conditions.

Following data analytics, the framework enters the preference learning stage. Here, the system constructs personalized preference models by combining analytical results with historical decision records, explicit feedback, and implicit behavioral observations. Explicit feedback includes user ratings, rankings, and direct evaluations, whereas implicit feedback consists of browsing behavior, click patterns, interaction frequency, and recommendation acceptance. By continuously analyzing these interactions, the framework learns individual priorities, identifies changing decision tendencies, and models the evolution of user preferences. As a result, the system develops personalized preference representations that more accurately reflect users' current decision-making behavior.

The next stage is the adaptive update, which represents the core innovation of the proposed framework[22]. Instead of relying on fixed decision models, the Adaptive Learning Engine continuously updates preference weights, decision criteria, and recommendation strategies whenever new behavioral information becomes available. Incremental and online learning techniques enable the framework to incorporate new knowledge efficiently without rebuilding the entire model. In addition, contextual adaptation allows the system to respond dynamically to changes in organizational objectives, environmental conditions, temporal factors, and user characteristics. This adaptive capability ensures that decision models remain current and responsive to evolving situations.

Based on the updated preference models, the framework proceeds to the recommendation stage. The Decision Intelligence Engine integrates adaptive preference information with predictive analytics, optimization algorithms, and multi-criteria decision-making methods to evaluate available alternatives. Decision options are ranked according to learned user preferences, contextual conditions, and organizational objectives before personalized recommendations are generated. To improve transparency and user confidence, each recommendation is accompanied by interpretable explanations describing the reasoning process, influential features, and confidence level associated with the recommendation.

Following recommendation delivery, the framework enters the feedback stage, where user responses are continuously collected. Feedback may be explicit, including ratings, evaluations, questionnaires, and preference adjustments, or implicit, such as click behavior, browsing duration, navigation patterns, interaction frequency, and recommendation acceptance. These feedback signals provide valuable information regarding recommendation quality, user satisfaction, and behavioral changes, enabling the system to assess the effectiveness of previous decisions.

The final stage is continuous learning, where feedback information is incorporated into the Knowledge Update and Adaptive Learning components. Newly acquired behavioral knowledge is integrated into user preference models, analytical patterns are refined, and recommendation strategies are continuously improved. Every interaction contributes additional learning, allowing the framework to enhance personalization, improve recommendation accuracy, and adapt to changing decision environments without requiring manual intervention. Consequently, the decision process forms a closed-loop learning cycle in which recommendations continuously evolve alongside user preferences and organizational contexts.

3.4 Comparative Analysis

Traditional Decision Support Systems primarily rely on predefined rules, mathematical models, and manually configured decision criteria. Although these systems are effective for solving structured and semi-structured decision problems, they generally assume that user preferences remain constant over time. Consequently, they lack the ability to adapt to changing user requirements, evolving organizational objectives, or dynamic environments. Furthermore, traditional DSS provide limited personalization, rarely incorporate continuous learning, and do not utilize user feedback for model improvement. These limitations reduce their effectiveness in modern decision environments characterized by rapid changes and large volumes of heterogeneous data.

Recent AI-based Decision Support Systems overcome several of these shortcomings by incorporating machine learning, predictive analytics, and data mining techniques[23]. AI-DSS can process large-scale datasets, identify complex patterns, and generate more accurate predictions than conventional systems. However, many existing AI-based solutions primarily focus on prediction accuracy rather than continuously adapting user preferences. In addition, numerous AI models operate as black-box systems with limited explainability, making it difficult for users to understand how recommendations are generated. Continuous feedback mechanisms and lifelong learning capabilities are also only partially implemented in most existing AI-DSS.

The proposed ID-DSS framework extends current AI-based approaches by integrating Adaptive Preference Learning as the central component of decision intelligence[24]. Rather than relying on static decision criteria or fixed predictive models, the framework continuously updates user preference models through explicit feedback, implicit behavioral observations, contextual information, and incremental learning techniques. Recommendation strategies therefore evolve alongside user behavior, resulting in higher personalization, improved recommendation relevance, and greater adaptability. Furthermore, the incorporation of an Explanation Engine enhances transparency by providing interpretable recommendations supported by feature importance, reasoning processes, and confidence scores. The continuous feedback loop further enables lifelong learning, allowing the framework to refine organizational knowledge and improve decision quality over time. Table 1 summarizes the comparison between Traditional DSS, AI-Based DSS, and the proposed Intelligent Data-Driven Decision Support System.

Table 1.
Comparative Analysis of Decision Support System Approaches

Feature	Traditional DSS	AI-Based DSS	Proposed ID-DSS Framework
Static Rule-Based Decision Model	Yes	Partial	No
Adaptive Preference Learning	No	Limited	Yes
Continuous Learning Capability	No	Partial	Yes
Personalized Recommendations	Limited	Moderate	High
Explainability	Low	Medium	High
Continuous Feedback Loop	No	Partial	Yes
Context Awareness	Limited	Moderate	High
Data-Driven Analytics	Partial	Yes	Yes
Real-Time Adaptation	No	Limited	Yes
Incremental Learning	No	Limited	Yes
Online Preference Updating	No	Limited	Yes
Human-Centered Decision Support	Limited	Moderate	High
Behavioral Learning	No	Partial	Yes
Decision Transparency	Low	Medium	High
Recommendation Accuracy Over Time	Static	Moderate	Continuously Improving
Knowledge Base Evolution	Manual	Partial	Automatic
Scalability	Moderate	High	High

Support for Dynamic Environments	Limited	Moderate	High

The comparison demonstrates that the proposed framework offers several significant improvements over existing Decision Support Systems. Unlike traditional DSS, it does not rely on static decision rules but continuously updates decision models through adaptive preference learning. Compared with current AI-based DSS, the proposed framework provides stronger personalization, comprehensive explainability, continuous feedback integration, online preference updating, and lifelong learning capabilities. These characteristics enable the framework to maintain recommendation quality even when user preferences and organizational contexts evolve over time.

3.5 Comparison with Previous Frameworks

Traditional Decision Support System frameworks primarily emphasize rule-based reasoning, mathematical optimization, and multi-criteria decision-making techniques. These systems have been successfully applied in domains such as healthcare, finance, manufacturing, and public administration. However, their decision models are generally predefined during system development and remain static throughout system operation. As organizational priorities and user preferences evolve, these frameworks require manual modification of decision criteria, limiting their flexibility and adaptability in dynamic environments[25]. Furthermore, conventional DSS rarely incorporate behavioral learning or continuous feedback mechanisms that allow recommendations to improve automatically over time.

Recent AI-based decision support frameworks have introduced machine learning, deep learning, and predictive analytics to improve recommendation accuracy and automate decision-making processes. These frameworks are capable of processing large-scale heterogeneous datasets and discovering complex relationships that are difficult to identify using conventional analytical methods. Nevertheless, many AI-based frameworks primarily optimize predictive performance rather than modeling continuously evolving user preferences. Their recommendation models are often trained offline using historical datasets and updated only periodically, making them less responsive to real-time behavioral changes. In addition, the widespread use of black-box learning algorithms reduces model interpretability, limiting user trust and organizational acceptance.

Existing recommender system frameworks represent another important development in intelligent decision support. Collaborative filtering, content-based filtering, hybrid recommendation models, and deep learning recommender systems have substantially improved recommendation quality across various application domains[26]. Despite these advances, many recommender systems focus primarily on predicting user-item interactions instead of supporting complex organizational decision-making. Preference representations are frequently derived from historical interactions without fully considering contextual changes, decision objectives, or evolving behavioral patterns. Consequently, recommendation quality may decline when user preferences change over time or when decision environments become increasingly dynamic.

Preference learning frameworks have also contributed significantly to personalized decision support by modeling individual preferences through ranking algorithms, pairwise comparisons, utility learning, and behavioral analysis. However, most previous studies concentrate on developing isolated preference learning algorithms rather than designing comprehensive decision support architectures. Continuous preference adaptation, knowledge management, explainable recommendations, contextual reasoning, and organizational decision intelligence are often treated as independent research topics instead of integrated framework components. As a result, many preference learning models remain difficult to implement within practical enterprise decision support systems.

The proposed framework distinguishes itself by integrating Adaptive Preference Learning as the central mechanism governing the entire decision-making process[27]. Instead of assuming static preferences, the framework continuously refines user preference models through explicit feedback, implicit behavioral observations, contextual information, and incremental learning techniques. This adaptive capability enables recommendation strategies to evolve automatically alongside changing user behavior, organizational priorities, and environmental conditions. Consequently, the framework supports lifelong personalization while maintaining recommendation relevance in highly dynamic decision environments.

Another distinguishing characteristic is the integration of a continuous feedback loop, which transforms the framework into a self-improving intelligent ecosystem. Every user interaction contributes additional knowledge that updates preference models, recommendation strategies, and organizational knowledge repositories. Unlike previous frameworks that rely on periodic retraining or manual model revision, the proposed architecture continuously incorporates new information through online and incremental learning mechanisms, enabling real-time adaptation without interrupting system operation.

The framework also places strong emphasis on Explainable Artificial Intelligence (XAI)[28]. While many existing AI-based decision support frameworks generate highly accurate predictions, they often provide limited insight into how recommendations are produced. The proposed framework incorporates a dedicated Explanation Engine that presents feature importance, reasoning processes, confidence scores, and preference contributions for every recommendation. This transparency enhances user trust, improves decision accountability, and facilitates human-AI collaboration during complex decision-making processes.

Furthermore, the proposed framework adopts a human-centered and context-aware perspective that is largely absent from many previous DSS architectures. Recommendations are generated not only from historical data but also by considering temporal conditions, organizational objectives, environmental contexts, behavioral evolution, and user-specific characteristics. This multidimensional understanding enables the framework to provide more relevant and personalized decision support across diverse application domains.

4. Conclusion

This study proposes a Foundational Framework for Intelligent Data-Driven Decision Support Systems (ID-DSS) Based on Adaptive Preference Learning (APL) to address the limitations of conventional Decision Support Systems in dynamic and data-intensive decision-making environments. Traditional DSS generally rely on static decision rules and fixed user preferences, while many AI-based decision support systems emphasize prediction accuracy without fully supporting adaptive preference learning, continuous feedback, explainability, and lifelong learning. These limitations reduce their ability to deliver personalized and adaptive recommendations in rapidly changing organizational contexts. Using the Design Science Research (DSR) methodology, this study develops a conceptual framework that integrates data-driven analytics, machine learning, adaptive preference learning, explainable artificial intelligence (XAI), continuous feedback, and knowledge updating into a unified architecture. The framework establishes a closed-loop decision-making process that continuously learns from user interactions, updates preference models, and generates personalized, context-aware, and explainable recommendations. The primary contribution of this research is the integration of adaptive preference modeling, continuous learning, decision intelligence, contextual awareness, and explainability within a single conceptual framework. Its main innovation, the Adaptive Preference Learning (APL) mechanism, continuously refines user preferences through explicit feedback, implicit behavioral observations, contextual information, and incremental learning. This capability enables the system to adapt automatically to evolving user behavior and decision contexts, thereby improving personalization, recommendation quality, and decision effectiveness. The proposed framework has broad application potential across domains such as healthcare, finance, manufacturing, education, e-commerce, smart cities, supply chain management, and public administration. Nevertheless, the study is limited to conceptual framework development and has not yet been validated through large-scale implementation or empirical performance evaluation. Future research should focus on prototype development, real-world implementation, and comprehensive experimental validation using benchmark datasets and organizational case studies. Further enhancement may also be achieved by integrating advanced technologies such as deep learning, Federated Learning, Explainable Artificial

Intelligence (XAI), Large Language Models (LLMs), and Multi-Agent Systems (MAS) to improve adaptability, scalability, transparency, and the overall intelligence of future decision support systems.

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