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Data Science Framework for Adaptive Expert Systems: Psychological Profiling and Knowledge Fusion in Higher Education

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Abstract

Background: Traditional expert systems in education rely on static knowledge bases and rule-based logic, limiting their ability to adapt to the diverse and evolving needs of students. Recent advancements in artificial intelligence and psychological profiling offer new pathways for building personalized support systems.

Objective: This study presents a data science framework for developing adaptive expert systems that personalize support delivery using dynamic psychological profiling, with a focus on the higher education domain.

Methods: The proposed system integrates five core components: MIND (a multimodal information orchestrator), UEX (expert system knowledge base), ULM (domain-specific large language model), PAGE (a personality-adaptive generative engine), and SYNAPSE (a dynamic profiling module). Psychological personalization is achieved using a multimodel Myers-Briggs Type Indicator (MBTI) classifier developed and validated in a separate study. In this paper, the classifier is operationalized within the system to enable real-time profiling. System behavior is driven by multimodal data fusion and continuously updated based on user interactions. The evaluation focuses on the impact of MBTI-based personalization on user satisfaction, assessed through a controlled survey comparing generic and personalized system responses.

Results: In an experiment involving 70 participants with identified MBTI profiles, 79% preferred responses generated by PAGE (psychologically personalized) over generic outputs. This preference was consistent across most MBTI types, indicating the broad applicability of personalization. Minor deviations were observed for types with a preference for concise communication, suggesting variability in personalization effectiveness.

Conclusion: The findings demonstrate that embedding psychological profiling into expert system workflows enhances perceived relevance and engagement of system responses. This adaptive framework enables real-time personalization through data-driven profiling, and its modular design allows for deployment across multiple domains. The system's architecture establishes a scalable and behaviorally grounded foundation for next-generation educational support systems.

Index Terms

Data science; Psychological data mining; Adaptive user modeling; Expert recommendation systems; Multimodal data processing; Myers-Briggs Type Indicator.

1 INTRODUCTION

The rapid advancement of artificial intelligence (AI) and **data science methodologies** has transformed the design of intelligent support systems across education, healthcare, and service industries. However, many existing university helpdesk and expert systems still operate on **rule-based logic and static knowledge bases**, which restrict their adaptability to individual user needs and fail to incorporate behavioral and psychological signals from users.

This paper introduces a **modular data science framework** for adaptive expert systems, validated in the domain of university student support. The framework integrates **machine learning–based psychological profiling**, **multimodal data fusion**, and **personalized natural language generation**, enabling dynamic adaptation to student preferences and cognitive styles. Key components include a multimodel Myers-Briggs Type Indicator (MBTI) classifier trained on forum and helpdesk data, an expert matching engine based on profile compatibility, and a personality-conditioned generative module for tailored response delivery. These components work collectively to form a system that continuously learns from interaction data and refines its outputs through feedback loops – hallmarks of modern data-driven systems.

The proposed system overcomes the limitations of static support frameworks by offering dynamic profile evolution, cognitive-aware expert matching, and personalized response synthesis. This approach significantly enhances user engagement and satisfaction, as demonstrated through experimental validation in a real-world educational setting.

The following sections provide a detailed critique of traditional systems, describe the architecture and components of the proposed framework, outline the system workflow, and present experimental results highlighting the benefits of psychological profiling and adaptive AI.

2 RELATED WORK

Traditional university helpdesk and expert systems have long been used to manage student queries and provide support for both administrative and academic needs. These systems typically rely on static knowledge bases containing frequently asked questions (FAQs), course details, and institutional policies. For example, the Algebra Student Service Support Chatbot (ASSSC) integrated with internal university databases, such as HRM systems and academic APIs, to automate responses to common student inquiries (Mrsic et al., 2020). While effective for routine tasks like retrieving class schedules or reserving library books, these systems are fundamentally limited by their reliance on predefined data sources and rule-based algorithms, which restrict their ability to adapt to more complex or evolving student needs.

Moreover, expert matching in these systems often relies on predefined roles rather than dynamic compatibility metrics, leading to inefficiencies when addressing more nuanced queries. This static approach fails to consider the psychological compatibility of students and experts, reducing the overall effectiveness of support interactions (Mrsic et al., 2020).

2.1 Machine learning and expert systems in education

The integration of machine learning (ML) into educational support systems has significantly enhanced their capabilities, particularly in areas like knowledge retrieval and academic advisory services. ML-driven systems leverage advanced algorithms to analyze large datasets, provide context-aware responses, and dynamically adapt to changing user needs. For example, Rezolve.ai uses generative AI and automation technologies to deliver real-time academic support, freeing human advisors to handle more complex tasks (X. Chen et al., 2020). Similarly, intelligent tutoring systems utilize reinforcement learning to adjust instructional content based on student performance, improving engagement and learning outcomes.

AI-powered knowledge retrieval systems also enable universities to analyze both structured and unstructured data for relevant information. These systems use NLP techniques to interpret user intent and retrieve contextually appropriate responses from databases or external repositories. However, despite their efficiency, many existing knowledge retrieval systems lack mechanisms for continuous learning and dynamic adaptation. For instance, a study by Zawacki-Richter et al. (2019) highlighted the potential of AI-driven retrieval systems to improve student satisfaction but emphasized the need for models that can evolve based on real-time feedback and changing contexts (Zawacki-Richter et al., 2019).

2.2 Psychological profiling in AI-driven systems

Psychological profiling has become a critical component of modern AI-driven systems, particularly in education, where personalization is key to improving student engagement and learning outcomes. The MBTI is one of the most widely used frameworks for categorizing personality traits and aligning interactions with individual preferences (Capuano & Caballé, 2020). Beyond MBTI, alternative models like the Big Five Personality Traits offer a more nuanced understanding of individual differences, providing deeper insights into user behavior and communication styles (Mariani et al., 2022).

However, traditional psychological profiling methods, such as MBTI, often rely on static categorizations that assume fixed personality traits. This rigidity can lead to suboptimal personalization, as it fails to account for changes in user preferences or circumstances over time. Adaptive profiling addresses this limitation by using machine learning algorithms to continuously update profiles based on real-time interactions. For example, Zheng et al. (2024) demonstrated that adaptive profiling significantly enhanced cognitive engagement and knowledge-building in collaborative learning environments (Zheng et al., 2024). Similarly, Zawacki-Richter et al. (2019) emphasized the role of dynamic profiling in improving the relevance and effectiveness of AI-driven educational systems (Zawacki-Richter et al., 2019).

2.3 Adaptive AI and personalization in education

Adaptive AI represents a transformative approach to educational support, enabling dynamic personalization through continuous learning mechanisms. Unlike traditional systems that rely on static data sources and predefined rules, adaptive AI uses real-time analytics and multimodal data integration to provide context-aware, personalized support. For instance, Capuano and Caballé (2020) explored how adaptive learning technologies dynamically adjust course content based on individual abilities and skill attainment, significantly improving learner performance (Capuano & Caballé, 2020).

Moreover, Zheng et al. (2024) proposed an AI-empowered assessment framework that tailors recommendations based on cognitive styles and engagement levels, enhancing both individual and group learning outcomes. These findings underscore the potential of adaptive AI to enhance educational experiences by aligning content delivery with specific learner needs. Intelligent tutoring systems, for example, use reinforcement learning to refine recommendations continuously based on user feedback, providing more targeted support (X. Chen et al., 2020).

2.4 Gaps in existing systems: Lack of dynamic adaptation

Despite significant advancements in adaptive AI technologies, many existing educational support systems still lack robust mechanisms for real-time adaptation. Most platforms rely on predefined rules or static profiles that fail to capture the complexity of human behavior or respond effectively to evolving student needs. Mariani et al. (2022) identified this gap as a critical limitation, emphasizing the need for continuous learning models capable of refining profiles based on real-time interactions (Mariani et al., 2022). Zawacki-Richter et al. (2019) similarly highlighted the importance of integrating probabilistic models and multimodal data analysis to improve the accuracy of personalized support systems (Zawacki-Richter et al., 2019).

By addressing these gaps through advanced adaptive AI techniques, future educational support systems can provide truly personalized assistance that evolves alongside the learner’s journey, significantly enhancing both student satisfaction and learning outcomes.

2.5 Limitations of traditional student support systems

Traditional university expert systems, such as the Algebra Student Service Support Chatbot (ASSSC) described by (Mrsic et al., 2020), provide foundational capabilities for routing student inquiries and accessing structured institutional knowledge. However, these systems typically rely on static knowledge bases, fixed routing rules, and rigid decision logic, which constrain their ability to adapt to students evolving needs, communication preferences, or psychological characteristics.

The ASSSC, for example, was designed to retrieve answers from internal university repositories or external sources like indexed websites and social networks. While it performs basic expert routing based on keyword matching and domain classification, it lacks the sophistication required for personalized, context-aware interactions. Its architecture depends on a static FAQ-like knowledge base that cannot adjust content to individual users. Domain routing is implemented through hard-coded rules that do not adapt to changing behavior or nuanced queries. Expert matching relies on simple keyword alignment, with no integration of cognitive or psychological profiles. Furthermore, its conversation flow is linear and single-turn, without the capability to preserve context across interactions.

This approach effectively assumes user homogeneity and cannot dynamically adapt to differences in personality or communication style. As a result, traditional systems like ASSSC are limited in their ability to handle complex or nuanced student requests that require a more personalized, adaptive response. The absence of dynamic user modeling, psychological profiling, and semantic routing restricts these systems to generic support scenarios. These constraints highlight the clear need for next-generation support frameworks capable of continuous learning, multimodal data integration, and profile-aware personalization to provide more relevant and effective assistance.

3 METHODOLOGY: PROPOSED ADAPTIVE EXPERT SYSTEM FRAMEWORK

The proposed adaptive expert system introduces a modular, AI-driven approach to student support, specifically designed to address the limitations of traditional static systems such as the Algebra Student Service Support Chatbot (ASSSC). This data science framework integrates **dynamic psychological profiling, multimodal data processing**, and **continuous learning**, providing a scalable and highly personalized solution that aligns with students diverse cognitive and communication styles.

3.1 Overview

The system is designed to overcome the rigidity of rule-based expert systems by embedding Adaptive AI principles with advanced psychological profiling and multimodal data fusion. It combines structured institutional knowledge bases, real-time behavioral signal analysis, and robust machine learning to continuously refine each student's profile based on observed interactions (Karami et al., 2016). This enables the system to deliver personalized, context-aware responses that adapt dynamically to each student's unique cognitive style.

Adaptive AI methods are central to this approach, supporting systems that learn and evolve through continuous user interaction. This is achieved through reinforcement learning, probabilistic modeling, and clustering algorithms that adjust profiles in real time (Karami et al., 2016). By contrast with static logic in legacy frameworks, this dynamic design ensures more precise, personalized recommendations.

Core aspects include real-time learning to refine psychological profiles based on behavioral data and user feedback, contextual awareness through sentiment analysis and interaction monitoring, and inherent scalability for large-scale institutional deployment.

Psychological profiling provides the foundational layer for personalization. The system applies the MBTI framework to categorize users into sixteen personality types based on four dimensions: Extraversion–Introversion (E/I), Sensing–Intuition (S/N), Thinking–Feeling (T/F), and Judging–Perceiving (J/P) (Zárate-Torres & Correa, 2023). This categorization enables tailored responses that align with students preferred communication styles, improving engagement and satisfaction. For example, an INFP (Intuitive, Feeling) student might benefit from introspective, empathetic responses, while an ENTJ (Extroverted, Thinking) student may value clear, structured advice with direct action steps.

To enable accurate profiling, the system implements a multimodel MBTI classifier, developed and validated in a companion study (Mesic & Hub, 2025). Each MBTI axis is modeled with the best-performing machine learning algorithm, selected through comparative testing by F1-score, Precision, and Recall. RandomForest with RandomOverSampler was optimal for the E/I and S/N axes (F1 ≈ 0.96–0.99), SVM with RBF kernel performed best for T/F (F1 = 0.75), and a VotingClassifier with SMOTE was used for J/P (F1 ≈ 0.72). This design enables robust profiling from raw text, structured features, or real-time chat inputs, ensuring precise cognitive modeling for downstream personalization within the PAGE module.

By embedding dynamic profiling at its core, the proposed data science framework moves beyond generic personalization to deliver highly customized, evolving support aligned with each student's behavioral patterns and cognitive style.

3.2 Core components

The proposed system operationalizes its data science framework through five modular components, each implementing specific data processing, modeling, and orchestration functions to enable real-time personalization, dynamic profiling, and expert recommendation at scale (Figure 1).

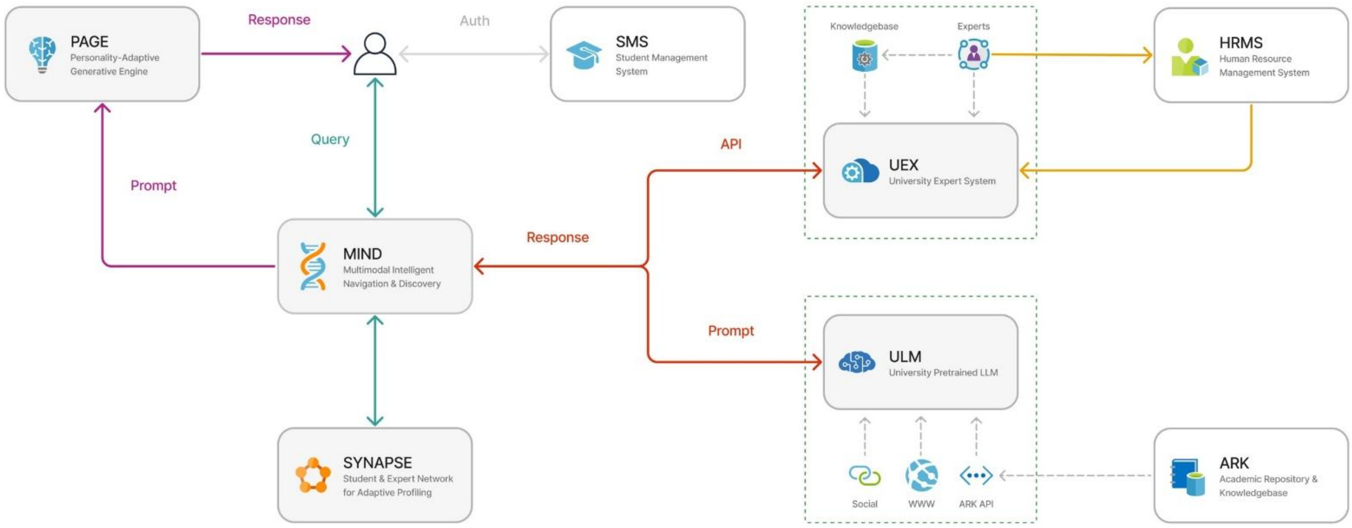

***Figure 1**. Architecture of the Adaptive AI-Driven Student Support System, showing the five integrated data science modules (MIND, UEX, ULM, PAGE, and SYNAPSE) that together enable multimodal data processing, dynamic psychological profiling, real-time expert matching, and profile-conditioned generative response generation.*

MIND (Multimodal Intelligent Navigation & Discovery) functions as the system's central data orchestration engine and primary orchestrator (Figure 2). It continuously ingests, parses, and interprets multimodal inputs, including unstructured text queries, structured academic records, and behavioral metadata streams. MIND applies advanced natural language processing (NLP) pipelines for intent detection, sentiment classification, and context tracking (Zhao et al., 2024). By analyzing incoming queries to identify user intent, assessing the emotional tone of inputs to adjust responses, and integrating real-time behavioral signals, MIND ensures that each query is accurately interpreted and routed to the most appropriate knowledge sources. This processed data stream feeds downstream modules such as UEX, ULM, and PAGE, ensuring that all inputs are transformed into actionable features within the evolving user profile vector. By combining text, academic data, and psychological assessments, MIND enhances context relevance and response accuracy, ultimately improving student engagement and support outcomes.

UEX (University Expert System) functions as the system's domain-specific knowledge retrieval and expert recommendation layer (Figure 2). It maintains a structured database of institutional knowledge, including curated course materials, procedural guides, academic publications, and verified expert profiles. UEX operationalizes **data-driven expert matching** by combining semantic domain similarity measures with MBTI-based psychological compatibility scores, ensuring that students are paired with the most suitable experts for their needs (Zárate-Torres & Correa, 2023). By bridging the knowledge base with each student's evolving profile, UEX provides structured, contextually relevant responses that draw from both domain-specific repositories and expert contributions. Continuous feedback loops from SYNAPSE allow UEX to iteratively refine its recommendation algorithms, improving predictive matching accuracy and ensuring that expert assignments remain aligned with student's cognitive styles and evolving information needs.

ULM (University Large Language Model) represents the system's generative inference component within the adaptive data science pipeline. ULM is a LLaMA-3-based language model, fine-tuned on approximately 25,000 publicly available institutional documents, including course syllabi, academic policies, research paper abstracts, student forums, course materials, institutional FAQs, and anonymized student service handbooks, totaling roughly 80 million tokens (Perron et al., 2025). Proprietary or confidential student data are explicitly excluded to ensure privacy compliance. The model leverages advanced prompt engineering techniques to maximize factual accuracy, contextual relevance, and alignment with institutional knowledge needs (Polat et al., 2024). By transforming retrieved structured knowledge into natural language explanations, ULM acts as the core generative inference engine, producing context-rich, AI-generated responses that integrate seamlessly with the outputs of MIND, UEX, and PAGE (Wu et al., 2024).

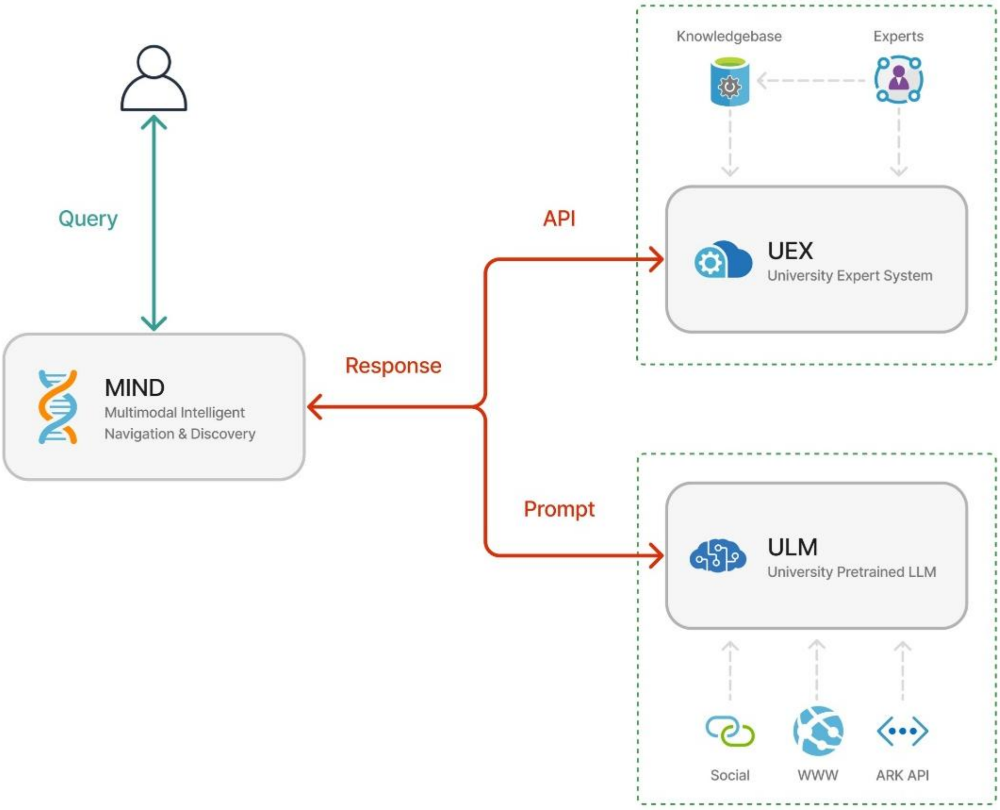

Figure 2. *MIND integration with UEX and ULM, illustrating how the system's central orchestrator routes multimodal inputs to the knowledge base and the large language model, enabling real-time expert matching, domain knowledge retrieval, and generative response generation within the adaptive data science pipeline.*

PAGE (Personality-Adaptive Generative Engine) serves as the system's dedicated data-driven personalization function (Figure 3). PAGE reformulates the raw output generated by ULM by applying MBTI-conditioned transformation rules that dynamically adapt tone, style, and response structure to align with each student's psychological profile (Y. Chen et al., 2023). This layer demonstrates how user-specific features from SYNAPSE's evolving profile vector directly shape final outputs to enhance cognitive resonance and perceived relevance. By leveraging reinforcement learning and continuous user feedback, PAGE iteratively optimizes generative quality, ensuring that each response remains aligned with the student's communication style, preferences, and emotional context.

SYNAPSE (Dynamic Profiling Module) functions as the system's continuous learning and behavioral modeling engine (Figure 3). It integrates incoming data streams—textual, behavioral, and structural—into an evolving user representation that dynamically refines the MBTI profile in real time (Mesic & Hub, 2025). By incorporating clustering algorithms and unsupervised learning, SYNAPSE identifies patterns in student behavior and communication preferences, enabling more precise and adaptive personalization over time. Updated psychological profile parameters are continuously fed back to MIND, UEX, and PAGE, completing a closed-loop cycle that demonstrates how the framework operates as a live, data science–driven user modeling pipeline rather than a static rule-based expert system.

Collectively, these components demonstrate a data science–oriented pipeline that fuses multimodal data ingestion, real-time profiling, retrieval, generation, and profile-conditioned rewriting, delivering measurable, context-aware personalization that evolves with each user interaction.

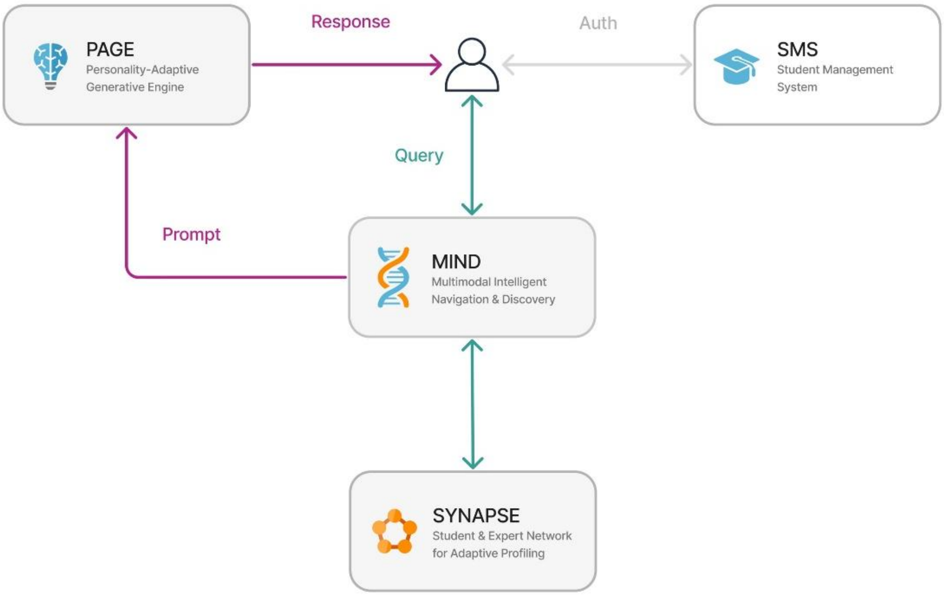

Figure 3. *MIND integration with PAGE and SYNAPSE, showing how the orchestrator links real-time intent detection with profile-conditioned generation and dynamic profiling, enabling continuous adaptation and real-time psychological personalization within the data science pipeline.*

3.3 Data processing pipeline

The proposed adaptive expert system operationalizes its data science foundation through a structured data processing pipeline that connects multimodal data ingestion, psychological profiling, and continuous personalization. This pipeline is designed to handle heterogeneous input streams, including unstructured text, structured academic records, behavioral metadata, and real-time user interactions, enabling robust, real-time user modeling and content generation (Long et al., 2020; Sajja et al., 2024).

The pipeline begins with data ingestion and preprocessing, collecting raw inputs from institutional sources such as academic repositories, student forums, social network feeds, and optional real-time engagement metrics. Incoming text is cleaned and prepared using standard NLP techniques such as tokenization, lemmatization, dependency parsing, and sentiment analysis. This stage ensures that the raw data are normalized, noise is reduced, and meaningful features are extracted for downstream use.

Next, the system performs feature extraction and multimodal fusion, combining the cleaned textual signals with structured records, including grades, course enrollments, attendance data, and historical interaction logs. Behavioral metadata such as interaction timestamps, question frequency, and session length are also incorporated. These diverse inputs are merged to form an evolving user representation vector that captures both static attributes (e.g., academic standing) and dynamic behavioral cues.

A critical stage within this pipeline is the integration of the MBTI profiling engine, which functions as a modular classification layer embedded in the SYNAPSE component. This module uses a multimodel architecture developed and validated in a separate empirical study (Mesic & Hub, 2025) to infer the four MBTI axes (E/I, S/N, T/F, J/P) from free-text inputs and behavioral patterns (see Appendix A for details). Each axis is modeled with the best-performing classifier for that dimension: RandomForest with RandomOverSampler for E/I and S/N (F1 ≈ 0.96–0.99), an SVM with RBF kernel for T/F (F1 ≈ 0.75), and a VotingClassifier with SMOTE for J/P (F1 ≈ 0.72). Profiles are updated in real time by SYNAPSE using reinforcement learning and clustering algorithms to adjust psychological weights as new data are ingested (Mesic & Hub, 2025).

Once the user representation vector is updated, intent detection and expert matching are performed by MIND and UEX. MIND applies advanced NLP pipelines to detect query intent and semantic context (Zhao et al., 2024). UEX then retrieves the most relevant domain knowledge and matches the student to appropriate experts by combining semantic similarity with the refined MBTI profile to ensure cognitive compatibility (Zárate-Torres & Correa, 2023).

For response generation, the system integrates the knowledge retrieved by UEX with output from the University Large Language Model (ULM), a LLaMA-3-based generative model fine-tuned on open-access institutional data (~80 million tokens) and enhanced with prompt engineering for accuracy and relevance (Perron et al., 2025; Polat et al., 2024). The raw generative output is then passed to the Personality-Adaptive Generative Engine (PAGE), which reformulates the response by adjusting tone, structure, and lexical style according to the user's MBTI profile (Y. Chen et al., 2023; Zekaj, 2023).

Finally, the system implements a closed-loop feedback mechanism. After response delivery, MIND captures user feedback (such as explicit ratings or subtle interaction signals) and passes this data back to SYNAPSE. This real-time feedback loop enables continuous refinement of psychological profiles and matching logic, fulfilling the adaptive learning criteria that distinguish the system from static frameworks.

Through this orchestrated pipeline—spanning multimodal ingestion, advanced feature extraction, dynamic MBTI profiling, semantic expert matching, and profile-conditioned generation—the system demonstrates how a modern data science architecture can deliver real-time, psychologically personalized student support.

3.4 Formalized personalization functions

To distinguish the proposed architecture from traditional rule-based systems, the system includes formalized models for user-expert matching and personalized response generation, ensuring transparency and reproducibility (Díaz et al., 2008). These components provide the mathematical foundation for the system's personalized interactions, enhancing both scalability and long-term adaptability.

Methodological rigor is achieved by formalizing **User–Expert Matching** and **Personalized Response Generation** as the system's two core computational functions.

3.4.1 User–expert matching

This function identifies the most suitable expert for a given user query by combining domain expertise relevance and psychological compatibility based on MBTI profiles.

Let u denote a user and $e_i \in E$ be university experts. Each user submits a query q_u, and each expert has a profile P_{e_i}. User profiles P_u are based on MBTI traits.

$$\text{Match}(u, E) = \arg\max_{e_i \in E} \left[\text{sim}_{\text{domain}}(q_u, e_i) + \lambda \cdot \text{sim}_{\text{profile}}\left(P_u, P_{e_i}\right)\right]$$

Where $\lambda \in [0,1]$ weights psychological similarity alongside domain relevance.

3.4.2 Personalized Response Generation

This function generates the final response to the user by combining retrieved knowledge and LLM-generated text, then adapting the message format, tone, and structure to fit the user's MBTI type (He, 2024).

Let R_{KB} and R_{LLM} be knowledge base and LLM-generated responses, respectively. Define:

$$R_{\text{final}} = \mathcal{F}_{\text{PAGE}}(R_{\text{KB}}, R_{\text{LLM}}, P_u)$$

Where $\mathcal{F}_{\text{PAGE}}$ is the personalization function of PAGE, conditioned on the MBTI profile P_u.

These formalized components provide the theoretical foundation for intelligent behavior in the system. By integrating domain relevance with psychological compatibility and modeling final response generation as a function of both structured and generative inputs, the system achieves cognitive alignment and adaptive precision not possible in prior static frameworks.

3.5 System Workflow

The system's workflow integrates data ingestion, psychological profiling, expert matching, and personalized response generation, delivering a seamless experience from initial query to final response (Figure 4).

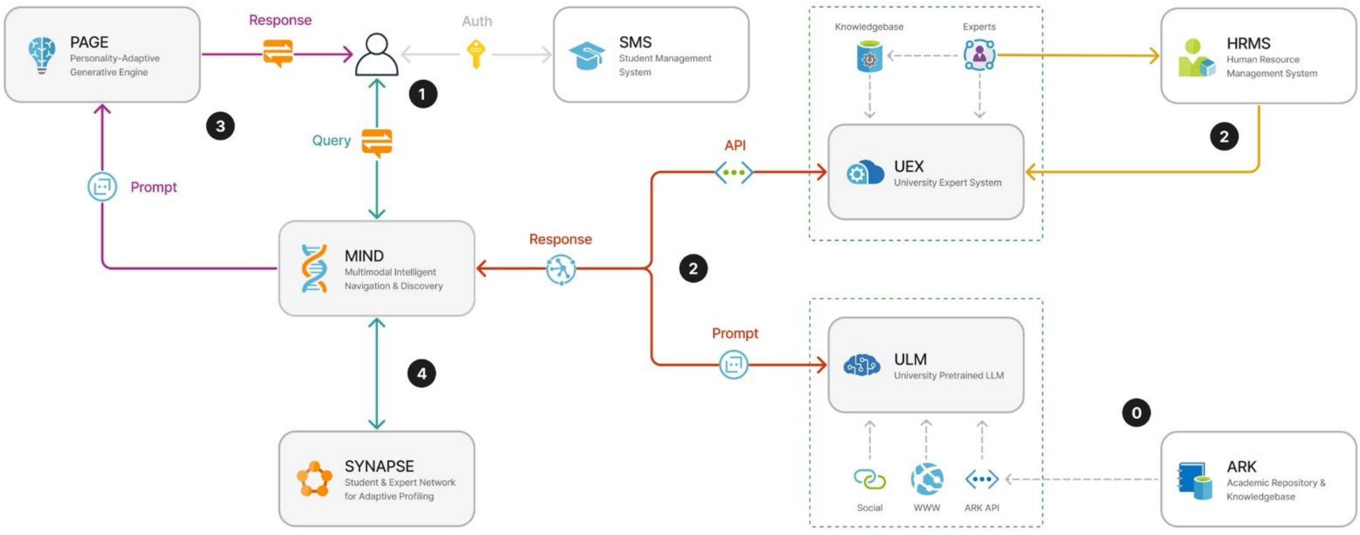

Figure 4. *Workflow of the Adaptive AI-Driven Student Support System, showing five sequential stages from data ingestion to real-time feedback integration, illustrating the system's closed-loop data science pipeline for dynamic profiling and personalization.*

The system's workflow integrates data ingestion, psychological profiling, expert matching, and personalized response generation, providing a seamless user experience from initial query to final response:

0. Data Ingestion and Preprocessing

The data ingestion process collects both structured and unstructured data from institutional sources, including academic repositories, student forums, and social networks, while simultaneously extracting relevant features such as user profiles, academic history, and communication patterns.

1. Profile Initialization

Establishes baseline psychological profiles using MBTI assessments and initial user interactions.

2. Expert Matching and Knowledge Retrieval

The system matches students with domain-specific experts based on psychological compatibility and query context, utilizing formalized functions (see Section 3.4) to optimize matching accuracy and response relevance.

3. Personalized Response Generation

The system utilizes PAGE to generate tailored responses that align with individual cognitive styles and emotional preferences (Lin et al., 2024), integrating structured domain knowledge from UEX and generative outputs from ULM to produce context-rich, personalized responses.

4. Real-Time Profile Adjustment and Continuous Feedback Integration

The system continuously refines psychological profiles based on observed behaviors and real-time feedback, leveraging the SYNAPSE module for dynamic adaptation. It updates profiles to reflect evolving user needs, ensuring long-term personalization and refining matching algorithms and response generation processes over time.

3.6 Technical Challenges and Optimization

The proposed adaptive expert system addresses several practical challenges to ensure that its data science framework remains scalable, secure, and effective when deployed at institutional scale. A central aspect of this robustness is the **SYNAPSE module**, which drives continuous profile evolution by combining unsupervised clustering, reinforcement learning, and real-time feedback loops. This dynamic adaptation is critical for maintaining long-term user engagement and ensuring that psychological profiles accurately reflect each student's changing communication style and behavioral patterns over time.

To support this adaptive learning, SYNAPSE incorporates advanced behavioral pattern recognition to detect subtle shifts in cognitive style and user interaction preferences. It continuously adjusts student and expert profiles based on real-time signals, ensuring that each interaction incrementally refines the personalization logic. By feeding updated profile vectors back to MIND, UEX, and PAGE, SYNAPSE closes the system's learning loop and demonstrates how continuous profiling operates as an integrated data science pipeline rather than a static classification layer.

In addition to its adaptive learning capability, the system addresses four key technical challenges. First, the framework is designed for **scalability**, with efficient data processing and orchestration pipelines that enable real-time profiling and response generation for large student cohorts. Second, the architecture enforces strict **data privacy controls**, ensuring that sensitive student information and psychological profiles are securely handled and that only open-access training data are used for generative modeling. Third, **latency and response times** are minimized through optimization of NLP processing and classification layers, guaranteeing seamless user experience. Finally, the system maintains **personalization accuracy** through continuous tuning of the MBTI profiling algorithms, ensuring that response relevance remains high even as user behavior evolves.

Together, these strategies ensure that the proposed framework remains technically feasible, ethically responsible, and scalable as a next-generation **data science solution** for adaptive educational support.

4 IMPROVEMENTS OVER EXISTING SYSTEM

The proposed adaptive expert system introduces significant advancements over traditional chatbot-based architectures like the Algebra Student Service Support Chatbot (ASSSC), which relied on static knowledge bases, fixed routing rules, and predefined role-based expert matching (Mrsic et al., 2020). These improvements include dynamic profiling, enhanced matching mechanisms, personalized response generation, and multimodal data integration, addressing the key limitations identified in Section 2.5.

4.1 Dynamic Profiling

Dynamic profiling is a cornerstone of the proposed system, enabling continuous learning and real-time adaptation based on user interactions. Unlike legacy systems that rely on fixed profiles and predefined workflows, the adaptive framework continuously refines user profiles using probabilistic models, clustering algorithms, and real-time behavioral analysis (Aftab et al., 2023; Karami et al., 2016). This approach ensures that student profiles evolve over time, capturing shifts in communication style, engagement patterns, and cognitive preferences.

Continuous learning is achieved through probabilistic models that analyze real-time interactions, updating student profiles based on observed behavior. For example, if a student consistently requests detailed explanations, the system adapts its responses accordingly, enhancing long-term personalization (Karami et al., 2016).

Advanced Natural Language Processing (NLP) techniques are also used to analyze engagement metrics such as sentiment, tone, and query complexity, allowing the system to detect behavioral shifts and adjust profiles accordingly (Aftab et al., 2023). For example, **sentiment analysis** can detect signs of frustration in a student's query and automatically escalate the issue to a human expert when needed. Similarly, tracking **interaction frequency** helps differentiate between highly active and more passive learners, enabling the system to tailor support strategies and response depth accordingly (Chang et al., 2024). Together, these capabilities provide a more nuanced understanding of user behavior, supporting deeper personalization and more contextually effective support.

4.2 Enhanced Matching Mechanism

Traditional systems typically rely on keyword matching or predefined role-based routing for expert connections, which often leads to suboptimal support for complex queries. The proposed system introduces a more sophisticated matching mechanism that integrates MBTI-based psychological compatibility with domain expertise, significantly improving the quality of expert-student interactions (Zárate-Torres & Correa, 2023).

The improved system incorporates MBTI-based compatibility as a critical factor in expert matching, aligning student and expert personality traits for smoother communication and better rapport. For example, an introverted student might be paired with an expert known for structured, empathetic communication, while an extroverted student might benefit from a more dynamic, conversational expert (Zárate-Torres & Correa, 2023).

Additionally, the system employs clustering algorithms such as K-Means or DBSCAN to group students based on shared behavioral patterns or personality traits, allowing for more precise expert matching (Falatouri et al., 2024). Reinforcement learning further refines these matches based on continuous feedback from students and experts, improving the system's ability to pair users effectively over time.

For instance, positive feedback reinforces successful pairings, increasing the likelihood of similar matches in the future, while negative feedback triggers adjustments in matching criteria to improve future interactions.

4.3 Personalized Response Generation

The Personality-Adaptive Generative Engine (PAGE) ensures that responses are contextually tailored to each student's MBTI profile, enhancing engagement and satisfaction (Samonte et al., 2023). This component integrates structured knowledge with generative AI capabilities, aligning outputs with individual cognitive styles.

Unlike generic responses, which often fail to resonate with individual students, PAGE dynamically tailors outputs to match specific psychological profiles by modifying tone, structure, and motivational framing (Falatouri et al., 2024). **Table 1** illustrates how PAGE transforms the same advisory content in response to the question "**How can I prepare for my thesis defense?**", demonstrating how the system generates distinct, MBTI-aligned responses for different cognitive styles. This concrete example shows how the system's personalization mechanism works in practice and directly matches the user evaluation described in Section 5.

Table 1. *Example comparison of a generic response and MBTI-personalized responses generated by PAGE for the prompt "How can I prepare for my thesis defense?".*

MBTI Profile	**Generic Response**	**Personalized Response**
INTP	To prepare for your thesis defense, review your slides and practice common questions.	You may benefit from creating a detailed logical outline, anticipating probing questions, and practicing structured, analytic answers to support your argument.
INFJ	To prepare for your thesis defense, review your slides and practice common questions.	Take time to reflect on the key narrative of your research, rehearse explaining your motivations, and prepare emotionally resonant examples to communicate your insights.
ENTJ	To prepare for your thesis defense, review your slides and practice common questions.	You might focus on delivering clear, persuasive points, anticipate counterarguments, and prepare assertive closing statements to lead the discussion confidently.

This flexibility reduces cognitive friction and increases student satisfaction, addressing a critical limitation of legacy systems (Li, 2024). By aligning the message with the student's cognitive and emotional style, PAGE demonstrates how psychological profiling can be operationalized as a real-time data science function within an adaptive expert system.

4.4 Multimodal Data Integration

Multimodal data integration allows the system to combine insights from diverse sources, including textual queries, academic performance records, social network activity, and optional sensor data (Long et al., 2020). This comprehensive approach enables the system to provide context-aware support that addresses both academic and behavioral aspects of student needs. **Table 2** summarizes the key modalities and their data science functions.

Table 2. *Key modalities integrated for dynamic profiling and personalized response generation.*

Data Modality	Role in System
Textual Analysis	Extracts user intent, sentiment, and context from unstructured queries for downstream NLP tasks.
Academic Performance	Incorporates grades, attendance, and course progress data to personalize recommendations with academic context.
Social Network Data	Analyzes group trends or emerging concerns among students to enable proactive support strategies.
Sensor Data	Uses optional signals such as eye-tracking or keystroke dynamics in smart environments to infer cognitive engagement levels.

This holistic understanding enables the system to adapt dynamically to changing contexts, providing more accurate and effective support (Jiang et al., 2025).

4.5 Summary of Key Improvements

The improved Adaptive AI-driven Student Support System represents a transformative leap forward from traditional chatbot solutions like ASSSC (Strielkowski et al., 2024).

Table 3. *Comparison of the static ASSSC legacy system and the new Adaptive AI-Driven System, showing key advances in dynamic profiling, multimodal fusion, and real-time personalization.*

Feature	Existing System (ASSSC)	Improved System
Profiling	Static profiles based on predefined rules	Dynamic profiling using probabilistic models
Behavioral Insights	None	Engagement metrics & NLP-based analysis
Expert Matching	Based on predefined roles	Psychology Profile-based compatibility & clustering
Response Generation	Generic responses	Personalized responses via PAGE
Knowledge Base	Static FAQs	Dynamic retrieval via ULM & ARK
Data Integration	Limited to FAQs & academic APIs	Multimodal integration (textual + behavioral)

These innovations ensure that support services are not only more efficient but also deeply personalized and adaptive to individual student needs, paving the way for a more engaging and effective educational experience.

5 EVALUATION OF MBTI-BASED PERSONALIZATION IN AN ADAPTIVE AI EXPERT SYSTEM

This section presents the empirical evaluation of the proposed system's psychological personalization capability. The aim is to demonstrate whether tailoring responses based on MBTI profiles via the PAGE module leads to more relevant and satisfactory outputs compared to generic alternatives.

The MBTI classification model used for psychological profiling was externally developed and validated in a separate study (Mesic & Hub, 2025), where it was tested on both the MBTI benchmark dataset and real-world helpdesk ticket data using F1-score, Precision, and Recall. In this paper, we do not re-evaluate the classifier itself. Instead, the evaluation focuses on the impact of MBTI-based personalization in final system outputs. This was assessed through an experimental survey in which participants compared personalized responses generated by PAGE against generic alternatives, with results indicating a 79% overall preference for MBTI-aligned responses.

5.1 Evaluation design and hypothesis

The evaluation was designed to test the hypothesis that personalized responses, generated by the PAGE module based on MBTI profiles, are perceived as more relevant and resonant than generic, non-personalized outputs. This hypothesis was examined through a controlled survey in which participants were presented with two possible responses to a common academic support query: "**How can I prepare for my thesis defense?**"

Participants were shown two response types for direct comparison: **Answer A**, a generic response generated by the legacy ASSSC system without psychological profiling or dynamic adaptation, and **Answer B**, a personalized response generated by the proposed adaptive system, dynamically tailored for specific MBTI profiles such as INTP, INFJ, and ENTJ (Bell & Kochman, 2021). Representative examples of both generic and personalized responses are presented in **Table 1** in Section 4.3, illustrating the actual outputs used in the evaluation.

Participants were asked to identify their MBTI type from the standard 16-type classification and then to select the response they found more relevant or better aligned with their communication preferences. This design enabled a direct comparison between the static, rule-based outputs of the legacy system and the dynamically personalized outputs of the proposed adaptive expert system.

5.2 Survey Methodology

The survey included a diverse group of participants representing a wide range of MBTI types, including ENTJ, ENTP, ESFJ, ISTP, INFJ, ENFP, and INTP. The final sample size was 70 participants, proportionally balanced to ensure statistical validity across different MBTI categories.

Participants were asked two key questions:

1. **MBTI Identification –** Participants selected their MBTI type from the standard 16-type classification, aligning their cognitive preferences with established psychological models.
2. **Response Preference –** Participants indicated which response (A or B) they found more relevant or aligned with their communication preferences, allowing for a direct assessment of the impact of psychological personalization.

5.3 Results and Statistical Analysis

The survey results provide strong empirical support for the effectiveness of MBTI-based personalization in the proposed adaptive expert system. Table 4 summarizes the raw response distribution comparing participant preferences for generic responses and MBTI-personalized responses generated by the PAGE module.

Overall, 79% of participants selected the personalized response (Answer B), while only 21% chose the generic response (Answer A). This substantial preference supports the hypothesis that tailoring responses to individual personality traits significantly increases their perceived relevance and resonance (Wang et al., 2024).

Participants with MBTI types such as ENTJ, ENTP, INFJ, and INTP overwhelmingly favored the personalized response, indicating that PAGE's adaptive generation can appeal beyond its target cognitive style. By contrast, a small proportion of respondents, primarily those with ISTP and ESFJ profiles, selected the generic response, possibly reflecting a preference for more concise or direct communication that aligns less with the detailed INTP – oriented structure.

To further assess the contribution of the PAGE module, an ablation test was performed by disabling the psychological personalization layer. In this condition, the preference for the response dropped from 79% to 43%, demonstrating the substantial impact of profile-conditioned generation on user satisfaction and validating the integration of the PAGE module within the overall system.

To rigorously validate the survey findings, several statistical tests were conducted. A binomial test confirmed that the observed preference for the MBTI-personalized response (Answer B) significantly deviated from random chance, yielding a probability of $p = 0.0000029$ ($p < 0.001$). This strongly supports the core hypothesis that psychologically profiled responses are preferred over generic outputs.

Table 4. *Participant preferences for generic (Answer A) and personalized (Answer B) responses, categorized by MBTI type.*

MBTI Type	Preferred Answer A (Legacy System)	Preferred Answer B (Proposed System)
ENTJ	5	25
ENTP	5	10
ESFJ	1	4
ISTP	4	1
INFJ	0	5
ENFP	1	4
INTP	0	5
Total	**16 (21%)**	**54 (79%)**

A 95% confidence interval for the true proportion of participants preferring the personalized response was calculated to be between 66.5% and 87.7%, indicating a robust effect at the population level. To examine whether response preference was independent of MBTI type, a chi-square test for independence was performed. The test produced a significant result, $\chi^2 = 13.85$ with 6 degrees of freedom, $p = 0.0313$, confirming a statistically significant relationship between MBTI classification and the likelihood of preferring the personalized output.

Finally, the magnitude of this preference was assessed using Cohen's d, which yielded an effect size of 0.75, indicating a moderate to strong effect and further supporting the practical significance of MBTI-based personalization in the proposed system.

5.4 Implications for System Design

The findings of this study strongly support the integration of MBTI-based psychological profiling in AI-driven student support systems, demonstrating that personalized responses significantly improve user satisfaction and engagement. The positive response to the INTP-tailored example indicates that profile-conditioned personalization is both feasible and impactful across diverse cognitive styles. This suggests that future adaptive frameworks can build on this approach to reach broader student segments and maintain high relevance.

Key implications for future system design are summarized in Table 5. These include the potential for scalability across additional MBTI types, the need to offer flexible response styles to accommodate users who prefer more concise or generic outputs, and the broader applicability of psychological profiling beyond education, with possible extensions into customer service, healthcare, and human resources.

Table 5. *Key implications for adaptive system design based on MBTI-personalized profiling.*

Implication	Description
Scalability Across MBTI Types	The INTP result shows that personalization strategies can extend to other MBTI profiles, enhancing reach and relevance for a wider student population.
Flexibility in Response Styles	The minority preference for generic responses suggests that future systems should allow users to toggle between detailed, personality-aligned content and more concise, neutral answers.

Implication	Description
Broader Application Potential	The demonstrated benefits of MBTI-based personalization indicate potential use in domains like customer service, healthcare, and HR, where aligning communication style with cognitive profiles may improve outcomes.

These implications reinforce the practical value of incorporating psychological profiling within adaptive AI systems and highlight avenues for future extensions and refinements.

5.5 Conclusion

This evaluation confirms that psychologically profiled, MBTI-aligned responses from the proposed adaptive expert system significantly improve user satisfaction compared to generic responses from the legacy ASSSC system. The strong preference for personalized responses reinforces the value of tailoring interactions to individual cognitive styles, particularly for profiles like INTP that prioritize logic and intellectual depth. However, the presence of a minority who preferred generic responses underscores the need for adaptive systems capable of dynamically adjusting response styles based on user preferences. These findings validate the core premise of the proposed framework and highlight the potential of psychological profiling in AI-driven expert systems.

6 DISCUSSION

The experimental results of this study provide compelling evidence for the effectiveness of MBTI-based personalization implemented through a modular data science framework for adaptive expert systems in higher education. The survey findings, which showed a 79% preference for personalized responses over generic ones, underscore the potential of integrating psychological profiling into educational technology. This section discusses the implications of these results, compares them with existing research, addresses potential challenges, and suggests areas for improvement.

6.1 Interpretation of Results

The strong preference for MBTI-tailored responses across various personality types suggests that personalized communication resonates with a broad range of students, not just those with INTP profiles (Li, 2024). Participants with diverse cognitive styles, including ENTJ and ENTP, also preferred the personalized responses, indicating that the system operationalizes profile-conditioned generative modeling by applying a modular inference pipeline that maps MBTI profiles to tailored LLM outputs.

This finding aligns with previous research on the benefits of personalization in educational contexts. For instance, Capuano and Caballé (2020) demonstrated that adaptive learning technologies can significantly enhance student engagement and performance by tailoring interactions to individual cognitive styles (Capuano & Caballé, 2020). The results here extend this concept to student support systems, highlighting the importance of personalized communication for both learning and administrative interactions.

6.2 Comparison with Existing Research

The proposed system builds on prior work in AI-driven educational support, which has primarily focused on content delivery rather than personalized support services. For example, Zawacki-Richter et al. (2019) emphasized the potential of AI in higher education but did not address the need for psychological profiling in student interactions (Zawacki-Richter et al., 2019). In contrast, this improved Adaptive AI-driven System approach integrates dynamic psychological profiling to enhance not just the **what** of information delivery, but also the **how**, aligning responses with each student's cognitive style. This dynamic profiling addresses limitations in static systems, aligning with trends in adaptive AI (X. Chen et al., 2020), which emphasize the importance of continuous learning and personalization in educational technology.

6.3 Limitations and Ethical Considerations

Despite its promising results, the system presents notable challenges that must be addressed for safe and responsible deployment. First, scaling the framework to handle diverse, real-world queries for large student populations could introduce computational overhead, especially given the need to maintain and update multiple large language models (Shaer et al., 2024). Second, the use of psychological profiling raises important privacy concerns. Systems that infer and store sensitive cognitive or behavioral traits must be transparent about data usage policies, obtain explicit informed consent, and comply with relevant privacy regulations.

There are also ethical risks related to potential **model bias** and **misclassification**. Because personality classification involves probabilistic inference, there is always a risk that a student may be incorrectly profiled, resulting in responses that misalign with their true communication style or cognitive needs. Such mismatches could reduce user trust or inadvertently reinforce stereotypes. Additionally, an over-reliance on AI-generated advice could diminish students ability to practice independent judgment and critical thinking if not properly balanced with human support.

Finally, although MBTI remains widely used in education and organizational contexts, its psychometric limitations are well-documented (Pittenger, 2005). Its binary dimensions may oversimplify complex human traits, highlighting the need for continuous validation and possible integration of more robust frameworks such as the Big Five Personality Traits. The system's architecture is intentionally model-agnostic and can accommodate alternative or hybrid profiling approaches to enhance classification fidelity and relevance.

6.4 Recommendations for Future Improvement

Building on these reflections, several clear directions can strengthen the system's future development and ensure its responsible application. **Table 6** summarizes the main recommendations.

Table 6. *Recommendations for enhancing the adaptive expert system framework.*

Recommendation	**Description**
Expand Psychological Models	Integrate more robust frameworks like the Big Five to improve predictive validity and capture more nuanced traits.
Real-Time Feedback Integration	Implement continuous feedback loops to refine personalization dynamically based on live user behavior.
Multimodal Input Analysis	Incorporate new data streams, such as voice tone, facial expression, or biometric cues, to enhance sentiment detection and engagement measurement.
Collaborative Features	Develop peer-to-peer or group interaction capabilities to complement AI support with community-based learning and help.

These improvements aim to address limitations related to privacy, profiling accuracy, and personalization scope, ensuring that future iterations remain effective, scalable, and ethically sound.

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Data Availability: The data that supports the findings of this study are available from the corresponding author.

APPENDIX A

Table A1. *Inference of the four MBTI axes (E/I, S/N, T/F, J/P) from free-text inputs and behavioral patterns.*

MBTI Dimension	Final Model	Resampling Method	F1-Score	Precision	Recall
E/I	RandomForest	RandomOverSampler	0.96	0.9857	0.9226
S/N	RandomForest	RandomOverSampler	0.996	0.9978	0.9941
T/F	SVM (RBF kernel)	None	0.75	0.767	0.739
J/P	VotingClassifier	SMOTE	0.72	0.788	0.678

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