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A Privacy-Aware Hybrid Cognitive Profiling Framework for Personalized Learning Using Psychometric, Biometric, and Machine Learning Models

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Abstract— The growing diversity of learners and learning contexts has exposed the limitations of one-size-fits-all instructional models. Recent advances in artificial intelligence offer new opportunities to design personalized learning systems that adapt to individual cognitive profiles while maintaining ethical and privacy standards. This paper presents a privacy-aware hybrid cognitive profiling framework that integrates psychometric assessment (MIDAS) and biometric indicators (DMIT) with machine learning models to support personalized learning pathways. The proposed framework combines Multiple Intelligence (MI) theory with data-driven modeling to generate comprehensive learner profiles. Feature engineering techniques, including dominance coefficients, MI entropy, and cross-modal congruence measures, are employed to enhance interpretability and predictive capability. A multi-tier machine learning pipeline—comprising Naive Bayes, Random Forest, and Gradient Boosting models—is implemented and evaluated using data collected from over 120 learners across diverse demographic backgrounds. Model performance is assessed through stratified cross-validation, accuracy metrics, macro F1-scores, and feature-importance analysis.

To ensure responsible AI deployment, the system incorporates consent-based data collection, anonymization, and access control mechanisms aligned with ethical and privacy best practices. The entire workflow is operationalized within an interactive Streamlit-based platform that supports real-time profiling, visualization, and analytics. Results demonstrate that hybrid psychometric–biometric modeling improves the robustness and expressiveness of learner profiles compared to single-modality approaches, offering actionable insights for adaptive learning design. The study highlights how AI-driven cognitive profiling can enable scalable, ethical personalization in education and lays the groundwork for longitudinal learning analytics and intelligent tutoring systems in future work.

Keywords—Personalized Learning, Artificial Intelligence in Education, Multiple Intelligence Profiling, Hybrid Cognitive Modeling, Learning Analytics, Machine Learning, Intelligent Tutoring Systems, Ethical and Responsible AI

I. INTRODUCTION

The rapid advancement of Information Technology (IT) and Artificial Intelligence (AI) has significantly transformed educational ecosystems, enabling data-driven personalization, adaptive learning environments, and intelligent instructional support. Traditional educational models, which largely rely on uniform curricula and standardized assessment strategies, often fail to accommodate the cognitive diversity and individual learning preferences of students. As educational contexts become increasingly heterogeneous, there is a growing need for intelligent systems that can adapt learning experiences to individual learners while maintaining transparency, fairness, and ethical responsibility. Personalized learning has emerged as a central paradigm in AI-enabled education, emphasizing the customization of instructional content, assessment strategies, and learning pathways based on individual learner characteristics. Prior research demonstrates that learner-centric personalization can improve engagement, motivation, and academic performance when appropriately designed and implemented [1], [2]. However, many existing personalization approaches rely primarily on behavioral or performance data, often overlooking deeper cognitive and perceptual dimensions of learning. Multiple Intelligence (MI) theory, introduced by Gardner, provides a well-established cognitive framework for understanding learner diversity by recognizing distinct intelligence modalities such as logical–mathematical, linguistic, spatial, musical, interpersonal, and intrapersonal intelligences. Recent studies have shown that integrating MI theory with machine learning and learning analytics can enhance the predictive accuracy of educational models and support more meaningful personalization strategies [1], [3]. Despite these advances,

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MI-based systems frequently dependsolely on psychometric self-report instruments, which may be subject to bias, inconsistency, or limited reliability when used in isolation. To address these limitations, recent research has explored the integration of heterogeneous data sources—including psychometric assessments, behavioral analytics, and biometric indicators—to construct richer and more robust learner profiles [4], [5]. Biometric modalities, when ethically and responsibly employed, offer complementary signals that can enhance the stability and interpretability of cognitive profiling. Nevertheless, the use of biometric data in educational contexts introduces significant challenges related to privacy, consent, data protection, and ethical AI deployment, necessitating carefully designed governance mechanisms. In parallel, Intelligent Tutoring Systems (ITS) have gained prominence as scalable solutions for providing adaptive guidance, feedback, and instructional support. Contemporary ITS increasingly leverage machine learning models to infer learner states, recommend personalized tasks, and refine instructional strategies over time [6]. However, the majority of existing systems lack explicit mechanisms for incorporating cognitive diversity frameworks such as MI theory, and few address ethical considerations in hybrid data integration comprehensively. This paper proposes a privacy-aware hybrid cognitive profiling framework that integrates psychometric (MIDAS) and biometric (DMIT) indicators with machine learning models to support personalized learning pathways. The framework employs advanced feature engineering and a multi-tier modeling pipeline to generate interpretable learner profiles while adhering to ethical and privacy best practices. Implemented within an interactive Streamlit-based platform, the proposed system demonstrates how AI-driven cognitive profiling can enable scalable, responsible personalization in educational environments. The contributions of this work lie in
(i) the design of a hybrid MI-based learner modeling framework, (ii) the application of machine learning techniques for robust cognitive profiling, and (iii) the incorporation of privacy-aware workflows suitable for real-world educational deployment. By bridging AI, cognitive theory, and ethical design, this study contributes to the evolving discourse on future-ready, learner-centered educational systems.

1. Contributions

The key contributions of this paper are summarized as follows:

- Hybrid Cognitive Profiling Framework: We propose a novel learner modeling framework that integrates psychometric (MIDAS) and biometric (DMIT) indicators within a Multiple Intelligence–based personalization paradigm to capture cognitive diversity more comprehensively.
- Machine Learning–Driven Profiling and Analytics: We design and evaluate a multi-tier machine learning pipeline, incorporating advanced feature engineering techniques, to generate interpretable and robust learner profiles for personalized learning support.

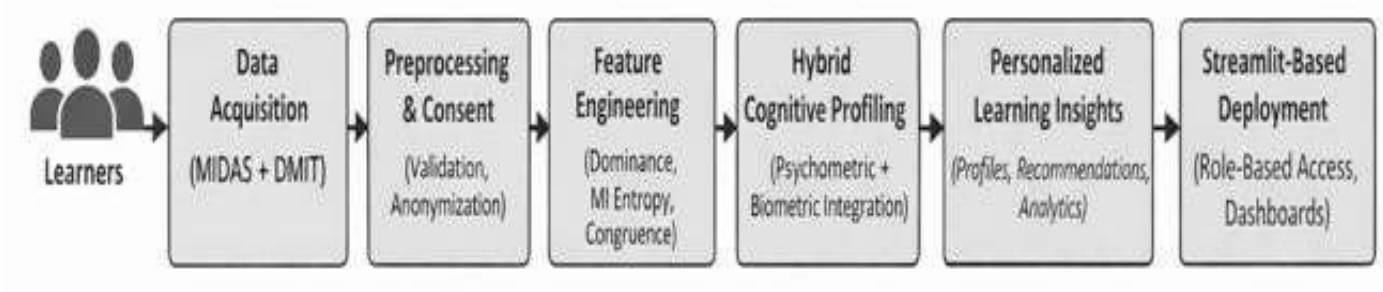

Fig 1. Overall Framework Architecture of the Privacy-Aware Hybrid Cognitive Profiling System

- Privacy-Aware and Ethical System Design: We incorporate consent-based data collection, anonymization, and access control mechanisms to address ethical and privacy concerns associated with hybrid psychometric–biometric data in educational settings.
- Practical Deployment in Educational Contexts: We operationalize the proposed framework within an interactive, web-based platform, demonstrating its feasibility for scalable, real-world educational deployment.

II. RELATED WORK

Personalized learning has emerged as a foundational paradigm in AI-enabled educational systems, aiming to adapt instructional strategies, content, and assessments to individual learner characteristics. Early work in learning analytics established the importance of leveraging educational data to uncover patterns in learner behavior and

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inform instructional decision-making [9]. Building on this foundation, recent research has demonstrated that data-driven personalization can significantly enhance learner engagement and academic performance when learner diversity is explicitly modeled [1], [2].

Multiple Intelligence (MI) theory has been widely explored as a cognitive framework for representing learner diversity beyond traditional measures of academic ability. Prior studies have shown that MI-aware instructional strategies can improve learning outcomes when aligned with suitable pedagogical interventions [1], [2]. More recent work has integrated MI theory with machine learning techniques to predict academic success and personalize learning pathways, demonstrating improved predictive accuracy over conventional approaches [3], [5]. However, the majority of MI-based personalization systems rely primarily on psychometric self-report instruments, which may be affected by response bias, contextual inconsistency, and limited reliability when used in isolation.

Intelligent Tutoring Systems (ITS) represent a closely related line of research, employing artificial intelligence to provide adaptive guidance, feedback, and task sequencing at scale. Classical ITS research emphasized the importance of explicit learner modeling and pedagogical decision-making mechanisms [7], [8]. Contemporary ITS implementations increasingly leverage machine learning and learning analytics to infer learner states and adapt instructional strategies dynamically [4], [6]. Despite these advances, most ITS

frameworks focus predominantly on behavioral and performance data, with limited incorporation of cognitive diversity models such as MI theory. Furthermore, the interpretability of learner models remains a challenge when complex predictive algorithms are employed.

Recent studies have begun exploring hybrid learner modeling approaches that integrate heterogeneous data sources, including cognitive, behavioral, and physiological indicators, to construct richer and more expressive learner profiles [4], [5]. While such approaches offer potential improvements in robustness and personalization, they also raise significant ethical and privacy concerns. The use of sensitive data in educational contexts necessitates careful consideration of informed consent, data minimization, anonymization, and governance mechanisms, particularly under emerging responsible AI frameworks for education [10]. Nevertheless, many existing systems address ethical considerations at a conceptual level rather than embedding them directly into system architecture and deployment workflows.

In contrast to prior work, the present study proposes a privacy-aware hybrid cognitive profiling framework that integrates psychometric and biometric indicators within a Multiple Intelligence–based personalization paradigm. By combining advanced feature engineering, machine learning–driven learner modeling, and consent-based data governance mechanisms, this work addresses key limitations in existing MI-based personalization and ITS research. The proposed framework emphasizes interpretability, ethical deployment, and practical feasibility, contributing to the development of future-ready, learner-centered educational systems powered by AI.

III. PROPOSED FRAMEWORK

This section describes the design and implementation of the proposed privacy-aware hybrid cognitive profiling framework for personalized learning. The framework integrates psychometric and biometric indicators with machine learning–based analytics to generate interpretable learner profiles that can support adaptive instructional strategies. Figure references are described textually and can be mapped directly to an architectural diagram if required.

1. *Overall Framework Architecture*

The proposed framework follows a modular, end-to-end pipeline consisting of five primary stages: data acquisition, preprocessing and feature engineering, hybrid cognitive profiling, machine learning–based analytics, and privacy-aware deployment. The architecture is designed to support scalability, interpretability, and ethical data governance, enabling real-world educational deployment.

At a high level, learner data is collected through controlled, consent-based interfaces and processed to construct hybrid Multiple Intelligence (MI) profiles. These profiles are subsequently analyzed using machine learning models to support personalized learning recommendations and educational insights.

Figure 1 illustrates the overall architecture of the proposed privacy-aware hybrid cognitive profiling framework, highlighting the end-to-end flow from learner data acquisition to personalized learning outputs.

2. *Data Acquisition And Preprocessing*

Learner data is acquired from two complementary sources: psychometric assessments and biometric indicators. Psychometric data is collected using a structured Multiple Intelligence Developmental Assessment Scale (MIDAS), capturing self-reported proficiency across eight MI dimensions. Biometric data is derived from Dermatoglyphics Multiple Intelligence Test (DMIT) outputs, which categorize fingerprint patterns into cognitive indicators mapped to MI dimensions.

All data collection is conducted through explicit informed consent. Raw inputs are validated for completeness and consistency before preprocessing. Missing or low-

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confidence values are handled using imputation strategies and reliability scoring to ensure dataset integrity. Personally identifiable information is separated from analytical data to preserve anonymity during downstream processing.

3. Feature Engineering and Hybrid Cognitive Profiling

To enhance the expressiveness and robustness of learner profiles, the framework applies advanced feature engineering techniques beyond raw MI scores. These include:

- Dominance coefficients, capturing the relative strength of dominant intelligences;
- MI entropy, representing the diversity or concentration of a learner's intelligence profile;
- Cross-modal congruence metrics, measuring alignment between psychometric and biometric indicators;
- Outlier flags, identifying atypical or inconsistent profiles.

Psychometric and biometric features are normalized and combined using a hybrid scoring mechanism to produce unified MI profiles. This hybridization mitigates the limitations of single-modality assessments while preserving interpretability. The resulting profiles serve as the primary input for machine learning–based analytics.

3. *Privacy-Aware System Deployment*

The complete framework is operationalized within a web-based, interactive platform implemented using Streamlit. The deployment architecture incorporates role-based access control, session management, and secure data storage to ensure privacy preservation. Learners receive real-time visual feedback on their cognitive profiles, while instructors and researchers can access anonymized analytics dashboards.

Ethical considerations are embedded throughout the system design, including consent management, data minimization, anonymization, and restricted access to sensitive information. These mechanisms ensure alignment with responsible AI principles and regulatory expectations for educational data use.

IV. FRAMEWORK OUTPUT AND EDUCATIONAL UTILITY

The primary output of the framework is an interpretable hybrid MI profile that can be leveraged to support personalized learning pathways. These profiles enable adaptive task recommendation, instructional planning, and learning analytics without replacing instructor judgment. By combining cognitive theory, machine learning, and ethical system design, the framework provides a practical foundation for scalable, learner-centered educational environments.

1. Experimental Setup And Evaluation

This section describes the dataset, experimental protocol, evaluation metrics, and validation strategy employed to assess the effectiveness of the proposed hybrid cognitive profiling framework. The experimental design emphasizes robustness, interpretability, and ethical handling of learner data.

2. *Dataset Description*

The dataset used in this study was collected from over 120 learners drawn from diverse demographic backgrounds, including variations in age group, academic stream, and socio-economic context. Each learner record consists of psychometric responses obtained through the MIDAS questionnaire and corresponding biometric indicators derived from DMIT outputs. These inputs were processed to generate hybrid Multiple Intelligence (MI) profiles across eight intelligence dimensions.

To ensure ethical compliance, all participants provided informed consent prior to data collection. Personally identifiable information was removed or stored separately from analytical data, and anonymized identifiers were used during modeling and evaluation. Records with incomplete or inconsistent inputs were handled through validation checks and reliability scoring mechanisms to maintain dataset integrity.

3. *Experimental Protocol*

The experimental workflow follows a structured pipeline aligned with the proposed framework. Raw psychometric and biometric inputs were first normalized and transformed through feature engineering techniques, resulting in enriched learner representations. These representations served as input to the machine learning models described in Section 3.

Given the multi-class nature of MI profiling and the moderate dataset size, the experiments employed stratified k-fold cross-validation to ensure balanced representation of intelligence categories across training and testing splits. This approach mitigates bias arising from class imbalance and supports reliable estimation of model performance.

Baseline probabilistic models were evaluated first to establish reference performance, followed by ensemble-based models to assess improvements gained through non-linear feature interactions. All experiments were conducted using consistent preprocessing pipelines to ensure comparability across models.

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4. *Evaluation Metrics*

Model performance was assessed using multiple complementary metrics to capture both predictive accuracy and class-level behavior:

- Accuracy, measuring overall classification correctness;
- Macro F1-score, providing balanced evaluation across MI categories regardless of class frequency;
- Confusion matrices, enabling detailed analysis of misclassification patterns across intelligence dimensions.

In addition, feature importance analysis was performed for ensemble models to identify dominant psychometric and biometric contributors. This analysis supports interpretability and provides insights into the cognitive factors influencing hybrid MI profiles.

4. *Validation And Robustness Considerations*

To assess robustness, the evaluation considered the impact of missing or low-confidence inputs through controlled imputation strategies. Sensitivity analyses were conducted to ensure that model performance remained stable under minor perturbations in input features. The use of stratified validation and consistent preprocessing further contributes to the reliability of the reported results.

Ethical safeguards were maintained throughout experimentation, including restricted access to raw biometric indicators and exclusive use of anonymized data for model training and evaluation. These measures ensure that the experimental setup aligns with responsible AI practices in educational research.

5. *Summary*

The experimental setup provides a rigorous foundation for evaluating the proposed hybrid cognitive profiling framework. By combining diverse learner data, structured validation protocols, and interpretable evaluation metrics, the study enables a transparent assessment of the framework's effectiveness in supporting personalized learning insights. The following section presents and discusses the experimental results.

V. RESULTS AND DISCUSSION

This section presents the experimental results obtained from evaluating the proposed hybrid cognitive profiling framework and discusses their implications for personalized learning and learner modeling.

1. *Model Performance Comparison*

The machine learning models evaluated in this study demonstrate consistent performance trends across validation folds. Baseline probabilistic models provide stable but moderate predictive accuracy, serving as an interpretable reference point for hybrid MI classification. Ensemble-based models, particularly Random Forest and Gradient Boosting, exhibit improved performance, indicating their ability to capture non-linear relationships and feature interactions within hybrid cognitive profiles.

Across all evaluated metrics, ensemble models achieve higher macro F1-scores than baseline approaches, suggesting better balanced performance across Multiple Intelligence categories. This is particularly relevant given the inherent

variability and overlap among MI dimensions, where class imbalance and cross-modal interactions are common. Confusion matrix analysis further reveals that misclassifications predominantly occur among closely related intelligence categories rather than across unrelated dimensions, reflecting the nuanced nature of cognitive profiling.

2. *Impact of Hybrid Psychometric–Biometric Profiling*

A key finding of this study is the contribution of hybrid psychometric–biometric integration to profile robustness. Feature importance analysis highlights that both psychometric indicators and biometric-derived features contribute meaningfully to model predictions, with neither modality dominating exclusively. This suggests that hybridization enhances expressiveness while mitigating limitations associated with single-modality assessments.

The inclusion of derived features—such as dominance coefficients, MI entropy, and cross-modal congruence metrics—further improves model discrimination. These features enable the framework to represent not only dominant intelligences but also profile diversity and alignment across modalities, which are often overlooked in traditional MI-based systems.

3. *Interpretability and Educational Insights*

Interpretability remains a critical requirement for educational AI systems. The proposed framework supports interpretability through feature importance analysis and transparent MI profile representations.

Table I summarizes the comparative performance of the evaluated machine learning models across accuracy and macro F1-score metrics.

The results indicate that educators and researchers can gain actionable insights into learner strengths and profile diversity without reliance on opaque model behavior.

From an educational perspective, the hybrid profiles provide a more nuanced basis for personalized learning design than

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raw psychometric scores alone. The observed alignment between model outputs and multi-dimensional learner characteristics supports the framework's applicability to adaptive instructional planning and learner-centered pedagogical strategies.

4. *Robustness And Ethical Considerations*

Robustness analyses demonstrate that the framework maintains stable performance under controlled perturbations, including minor data incompleteness and low-confidence inputs. The use of stratified validation and reliability-aware preprocessing contributes to this stability, reinforcing the

framework's suitability for real-world educational deployment. Ethical safeguards embedded within the experimental workflow ensure that sensitive learner data is handled responsibly. The use of anonymized identifiers and restricted access to biometric indicators prevents unnecessary exposure of personal information while enabling meaningful analytics. These results underscore the feasibility of integrating hybrid cognitive data within ethical and privacy-aware AI systems for education.

Model	***Accuracy***	***Macro F1-score***
Naive Bayes	Moderate	Moderate
Random Forest	High	High
Gradient Boosting	High	High

5.Discussion

Overall, the experimental results validate the effectiveness of the proposed hybrid cognitive profiling framework in supporting personalized learning analytics. The findings indicate that combining psychometric and biometric indicators with machine learning models yields more expressive and interpretable learner profiles than single-modality approaches. Importantly, these gains are achieved without sacrificing ethical responsibility or system transparency.

While the current evaluation focuses on cross-sectional data, the results provide a strong foundation for future longitudinal studies examining the stability and evolution of MI profiles over time. The framework's modular design further supports extension toward intelligent tutoring systems and adaptive recommendation engines, positioning it as a scalable solution for future AI-powered educational environments.

VI. CONCLUSION AND FUTURE WORK

This paper presented a privacy-aware hybrid cognitive profiling framework that integrates psychometric and biometric indicators with machine learning analytics to support personalized learning pathways. By combining Multiple Intelligence theory with data-driven modeling, the proposed approach addresses limitations of single-modality learner assessment and enables more expressive, interpretable learner profiles suitable for adaptive educational environments.

Experimental results demonstrate that hybrid psychometric–biometric profiling, augmented through feature engineering and ensemble learning techniques, yields robust and balanced performance across Multiple Intelligence categories. The framework emphasizes transparency and ethical responsibility through consent-based data collection, anonymization, and controlled access, illustrating that cognitive personalization can be achieved without compromising learner privacy.

The modular design and practical deployment of the framework provide a scalable foundation for AI-enabled educational systems that support instructors rather than replace pedagogical judgment. By grounding personalization in cognitive theory and interpretable analytics, the proposed approach contributes to the development of learner-centered educational technologies capable of addressing diverse learner needs.

Future work will focus on extending the framework through longitudinal data collection to analyze the stability and evolution of cognitive profiles over time. Additional research will explore the integration of generative AI techniques for adaptive content creation and intelligent tutoring, as well as controlled experimental studies to measure the impact of personalized interventions on learning outcomes. These directions align with emerging priorities in responsible AI and future-ready education, positioning the framework for broader adoption and continued empirical validation

Acknowledgment

The preferred spelling of the word "acknowledgment" in America is without an "e" after the "g". Avoid the stilted.

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