# Summary of Literature Review and Knowledge Gap - Table

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| Author(s) | Year | Key Findings | Limitations | Relevance to Current Study |
| Sihwail et al. | 2024 | Deep learning models achieve 94% accuracy using multimodal data fusion. | High computational requirements and complex implementation. | Informs the use of efficient, lightweight models for better scalability. |
| Ifenthaler & Yau | 2023 | Systematic review shows LA improves early warning by 30%. | Focus on theory over practical deployment in diverse institutions. | Highlights the need for a practical, deployable system. |
| Khan & Ghosh | 2022 | Meta-analysis confirms ensemble methods (Random Forest) are most accurate. | Models often lack interpretability for educators. | Guides algorithm selection and emphasizes model interpretability. |
| Sárvári & Csernoch | 2022 | Study highlights need for adaptive systems during educational disruptions. | Limited exploration of real-time data integration. | Supports the design of a system adaptable to changing environments. |
| Sharma et al. | 2021 | Multimodal data fusion improves prediction accuracy by 27%. | "Grey-box" approach not fully explored for user trust. | Validates the hybrid approach and the need for transparent AI. |
| Baker & Inventado | 2020 | Linking prediction to intervention reduces dropout rates by 22%. | Frameworks are often institution-specific and not generalizable. | Reinforces the aim to create a system with actionable insights. |
| Romero & Ventura | 2020 | Survey identifies hybrid models as top performers in EDM. | Many advanced models are not feasible for resource-constrained settings. | Justifies the hybrid model while focusing on resource efficiency. |
| Alyahyan & Düştegör | 2020 | Comprehensive feature sets boost accuracy by 18-25%. | Requires extensive, clean data which is often unavailable. | Informs robust feature engineering and data preprocessing steps. |
| Gibert et al. | 2020 | Hybrid AI models achieve up to 95% accuracy in classification. | High dependency on large, labeled datasets for training. | Guides strategies for working with realistic, imbalanced datasets. |
| Hussain et al. | 2019 | LMS engagement data improves prediction accuracy by 15-20%. | Model may not generalize across different LMS platforms. | Supports the inclusion of behavioral and engagement metrics. |
| Winne & Baker | 2018 | Tracking metacognition improves predictions by 25%. | Difficult to quantitatively capture and model metacognitive data. | Suggests the value of incorporating indirect proxies for self-regulation. |
| Alazab et al. | 2018 | Robust feature engineering is key to model performance. | Feature engineering process can be domain-specific and not transferable. | Highlights the importance of domain-specific feature selection for education. |
| Agudo-Peregrina et al. | 2017 | TAM model shows perceived ease of use drives adoption. | Does not address the integration of TAM principles into system design. | Informs the design of a user-friendly and easily adoptable system interface. |
| Daniel | 2016 | Identifies data integration and ethics as major hurdles for Big Data in HE. | Lacks a practical framework for overcoming these challenges. | Addresses the critical challenges of data integration and ethical AI from the outset. |
| Popenici & Kerr | 2016 | Emphasizes the need for ethical frameworks and explainable AI in education. | Lacks implementation guidelines for creating such systems. | Provides the ethical foundation for developing a transparent and trustworthy system. |
| Siemens & Baker | 2015 | Establishes the foundational principles of Learning Analytics (LA). | Early LA work focused more on analytics than on actionable interventions. | Grounds the study in the core objective of LA: to optimize learning and environments. |
| Okebukola et al. | 2015 | Highlights infrastructure challenges in Nigerian educational contexts. | Study is localized and does not propose a technical solution. | Ensures the system design is informed by the specific constraints of the target environment. |
| Eze et al. | 2015 | Analyzes patterns of e-learning facility utilization in Nigeria. | Focuses on adoption patterns, not on predictive analytics. | Provides contextual understanding of the technological landscape for deployment. |
| Adedoyin & Soykan | 2015 | Identifies key challenges in the rapid shift to online learning. | Does not develop tools to mitigate these challenges. | Underlines the importance of creating systems resilient to educational disruptions. |
| Blank | 2015 | Proposes strategic models for innovation implementation. | Framework is generic and not tailored to educational technology. | Offers a strategic lens for planning the development and deployment phases. |