International Journal of Applied Mathematics

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

HYBRID STRUCTURAL EQUATION MODELING AND MACHINE LEARNING APPROACHES FOR PREDICTING ACADEMIC OUTCOMES: A LITERATURE REVIEW IN IRAQI HIGHER EDUCATION E-LEARNING

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Abstract:

The rapid expansion of digital learning environments has highlighted the need for analytical models that can both explain and predict learner performance. Structural Equation Modeling (SEM) and Machine Learning (ML) have been widely applied in this domain, yet their separate use presents notable limitations: SEM offers strong theoretical grounding but limited predictive accuracy, while ML provides superior performance in nonlinear and high-dimensional contexts but often functions as a "black-box" with weak interpretability. This literature review synthesizes recent studies (2020–2025) on hybrid SEM–ML approaches for predicting academic outcomes, with a particular focus on higher education e-learning in Iraq. The review demonstrates that integrating SEM with ML augmented by explainable AI (XAI) techniques such as SHAP and LIME combines conceptual clarity with predictive robustness, enabling both actionable insights and reliable early intervention strategies. Despite significant global progress, Iraqi higher education continues to face critical challenges, including infrastructural deficits, digital readiness gaps, and fragmented e-learning policies, resulting in limited adoption of hybrid frameworks. This study contributes by mapping current advances, identifying methodological and contextual gaps, and proposing a context-sensitive SEM–ML model tailored to Iraq's transitional higher education sector. The findings underscore the potential of hybrid frameworks to enhance predictive learning analytics, improve academic outcomes, and inform policy reforms in under-resourced settings.

Received: August 08 2025

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Keywords: Structural Equation Modeling (SEM), Machine Learning (ML), Hybrid SEM–ML Framework, Academic Performance Prediction, Iraqi Higher Education E-Learning.

1. Introduction

1.1 Background and Context

The growth of e-learning increased recent adoption of digital platforms has revolutionized higher education globally, especially the era after the COVID-19 pandemic that facilitated the shift to a digital-based delivery [1,2]. And although these new approaches have generated enhanced accessibility and flexibility, they also revealed huge inequalities between infrastructures as well as digital readiness, pedagogical support and services among regions [3]. Some of these countries, such as the UAE and Saudi Arabia, have introduced artificial intelligence (AI), cloud-based platforms and learning analytics into national education strategies to modernize higher education [4]. On the contrary, Iraq's e-learning uptake seems to be more reactive and fragmented owing to a sense of crisis that the pandemic created rather than any premeditated designing [5,6]. Therefore, students and staff in Iraq still encounter lack of infrastructure, unstable internet access, and low readiness of institutions which lead to dissatisfaction, poor participation and weak academic achievement [7].

1.2 Problem Justification

To study drivers of success in e-learning, strong analytical tools that are capable to take into account psychological as well as behavioral characteristics on the part of learners need to be employed. Structural Equation Modeling (SEM) has been used to validate constructs such as motivation, engagement, satisfaction, and usability, providing both explanatory and confirmatory power [8,9]. But the predictive power of SEM is low, especially for nonlinear and high-dimensional educational applications [10]. On the other hand, Machine Learning (ML) methods like Random Forests [1], Gradient Boosting [2], Support Vector Machines (SVM) and deep learning show high predictive performance to predict academic outcomes but suffer from low interpretability owing theoretical knowledge [11,12]. Recent research has made strong claims for the rectification of these problems, which can be found by combining SEM and ML, in which a balance is struck between conceptual rigor and predictive robustness [13,14]. However, hybrid SEM–ML models have not yet been fully explored in transition and low-resource settings such as Iraq which is predominately data poor [15,16].

1.3 Purpose of the Paper

The paper is meant to offer a systematic review literature with synthesis of hybrid SEM–ML utilized for academic performance prediction in e-learning. Specifically, the research review integrates studies between 2020 and 2025 to investigate how SEM and ML have been used separately or in combination with reference to the Iraq higher education. By highlighting

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

methodological strengths and shortcomings, comparative strengths/weaknesses, and contextual constraints the paper positions the hybrid SEM–ML model as a promising framework for explicating and predicting learner outcomes in digital education settings.

1.4 Contribution and Significance

This paper has three major contributions. There are a couple of academic benefits to the paper: in the first place, it provides an academic contribution by placing hybrid SEM–ML models (models for predicting latent variables with optimization-based ML approaches) into the context of recent theoretical and empirical work on educational data science. Second, it underscores the policy and practical for implication of Iraq Educators; where loss of an evidence-based model due to gap in how it promotes students' engagement and therefore their success. Third, it posits that the extent to which the co-application of SEL, ML and XAI (eg., SHAP, LIME) tools in the Iraqi context is potentially novel as there is a paucity in regional literature on how this could potentially complement our understanding of under-resourced/transitional higher education systems.

2. E-Learning Landscape and Learner Perception Constructs

2.1 Global and Regional E-Learning Landscape

E-Learning has become an international phenomenon with the global e-learning market projected to be worth about $107 billion by 2015 .Technology advances, along with digital platforms and the unprecedented impact of COVID-19 pandemic, has accelerated rapid global spread for e-learning [17,18]. As of 2023, over 80% of universities in the world had provided learning management systems (LMS) and synchronous tools such as Zoom, Microsoft Teams, and Google Meet to educational environments [19]. Advanced platforms increasingly incorporate artificial intelligence, adaptive learning and analytics to personalize instruction and increase learner engagement [20].

In the Middle East, national leadership in education is driven by countries like the United Arab Emirates and Saudi Arabia who have leveraged AI mobility tools and adaptive analytics to form new technological strategies for higher education [21]. For the UAE, and Saudi Arabia the Mohammed Bin Rashid Smart Learning Program and FutureX initiatives are examples of how systems based on AI; development of faculty; QAFS can play a vital role in sustaining future to digital learning [22]. Qatar and Oman have adopted smart LMSs and adaptive dashboards to While Iraq has had a patchy and reactive uptake of e-learning, mostly its initiation was due to the COVID-19 crisis [24,25]. Iraqi universities including Baghdad and Kufa used Moodle, Google Classroom, and Zoom with little training, infrastructure or institutional strategies [26]. Such that, many students reported dissatisfaction, lack of motivation and high drop-out rates have found to accompany systemic and pedagogical weaknesses [27]. The underlined discrepancies emphasize the critical importance of contextually-appropriate frameworks that can improve academic success

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

in Iraq's deprived higher education setting [28]. Table 1: Comparison of e-learning strategies in the selected Middle Eastern countries, from year 2020 to year 2024. In contrast to the UAE, Saudi Arabia and Qatar which have progressed with AI-in-the-platform and national QA frameworks, Iraq has been left behind with an emergency driven fragmented implementation without organization-level support [17–28].

Table 1. E-Learning strategies and platforms in selected Middle Eastern countries (2020–2024).

Country	E-Learning Strategy / Platform	Methods Used	References (2020–2024)
UAE	Mohammed Bin Rashid Smart Learning Program; Blackboard, AI-enabled tools	Blended learning, smart classrooms, adaptive AI learning	[1], [39]
Saudi Arabia	FutureX , National eLearning Center; Blackboard, Moodle, Coursera	Mobile-first platforms, national QA frameworks, learning analytics	[4], [22]
Qatar	Qatar University Smart LMS (Blackboard Ultra); AI dashboards	Personalized learning, real-time analytics, instructor dashboards	[9], [39]
Oman	National Digital Education Strategy; Moodle, Zoom, MS Teams	Synchronous delivery, digital content platforms, faculty training	[39]
Bahrain	Bahrain eGovernment Portal; Moodle, Google Classroom	Asynchronous content, blended learning, teacher training initiatives	[39]
Iraq	Post-COVID adoption of Moodle, Google Classroom, Zoom	Emergency remote teaching, ad-hoc LMS training, perception surveys	[5], [7], [6]

2.2 Learner Perception Constructs in E-Learning

Learner perception is the focus of digital education research, as it includes cognitive, emotional and behavioral dimensions that influence academic achievement directly. The literature consistently highlights five fundamental constructs: motivation, engagement, satisfaction, system

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

usability and readiness [29,30]. A key issue for engagement and learning success in online settings is motivation, which affects persistence and self-regulation Self-Determination Theory (SDT) identifies autonomy, competence but also relatedness as important motivational factors [31]. Engagement consists behavior involvement, cognitive engagement and affective investment, has a positive relation with enhanced critical thinking skills, and retention and dropout in the digital classroom [32,33]. Satisfaction, as learners' global assessment of the system quality and perceived usefulness of the system, is highly related to system quality, perceived usefulness, and interaction with instructors and peers [34]. Ease and efficiency of using learning management systems (LMSs) for learners also lead to decreased cognitive load making participation comfortable, thereby aiding long-term retention of knowledge [35]. "Readiness" also refers to digital literacy, technical preparation and psychological self-confidence—but not computer experience—where it correlates with performance and reduced dropout likelihood [36]. These constructs have been validated at large scale through the use of Structural Equation Modeling (SEM), even though its restrictions in predicting achievements clearly shows the importance to complement it with Machine Learning (ML) techniques, able to model complex and nonlinear relationships within the educational domain [37,38].

At this point, a conceptual model is necessary that is to visualize how learners' perception constructs are related with academic results. Figure 1 shows the proposed model, which considers motivation, engagement and satisfaction as factors that determine system usability (or readiness) for learner performance in e-learning. The theoretical base underlying this discussion is revealed in this framework.

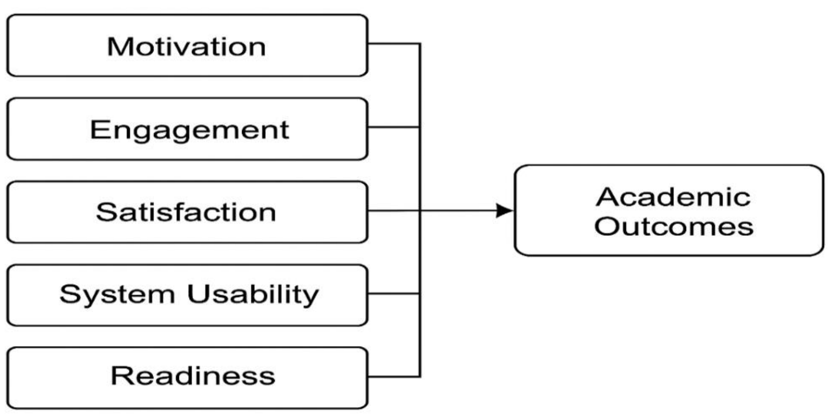

Figure 1conceptual Model linking learner perception constructs with academic outcomes.

Although learner perception constructs (e.g., motivation, engagement, satisfaction, system usability and readiness) that have been validated extensively in the e-learning literature are theoretically important, their predictive power is limited when estimated using traditional statistical methods alone. For instance, Structural Equation Modeling (SEM) has good explanatory

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

powers but is not always effective in handling nonlinear and high-dimensional data; Machine Learning (ML), on the other hand, has predictive discriminative power but can be theoretical “black-boxes.” To fill these methodological gaps, the following section critically examines the use of SEM, ML and hybrid SEM–ML techniques in educational research while comparing their advantages and shortfalls.

3.1 Structural Equation Modeling (SEM) in Education

Structural Equation Modeling (SEM) has been widely adopted in educational research as a robust method for analyzing relationships among latent constructs and observed indicators. Its primary strength lies in validating theoretical models that incorporate complex variables such as motivation, engagement, satisfaction, self-efficacy, and readiness, which are central to understanding student performance in e-learning environments [40]. Unlike traditional regression techniques, SEM can simultaneously assess measurement models and structural paths, offering both confirmatory and explanatory power [41].

Recent studies emphasize the versatility of SEM in higher education research. For example, PLS-SEM has been applied to examine the mediating effects of learner satisfaction on academic outcomes, highlighting the importance of usability and system quality in shaping educational experiences [42]. Similarly, SEM has been utilized to investigate the relationship between digital readiness and academic success, providing empirical evidence that institutional support and infrastructure are critical determinants of student engagement [43].

Furthermore, SEM has been increasingly integrated with modern learning theories such as Self-Determination Theory (SDT) and Technology Acceptance Model (TAM), allowing researchers to test models that combine psychological constructs with behavioral data from digital platforms [44]. However, despite its strengths, SEM has limitations in predicting nonlinear and high-dimensional data patterns typically found in learning management systems (LMS) and large-scale educational datasets [45]. This shortcoming underscores the necessity of complementing SEM with data-driven approaches such as machine learning, which are better equipped to uncover hidden patterns and optimize predictive performance.

3.2 Machine Learning (ML) in Academic Prediction

Machine Learning (ML) becomes the dominant way for forecasting academic performance [15, 30] given its efficiency in simultaneously processing big data which is nonlinear and high-dimensional. Unlike SEM, which is based on theoretical assumptions, ML uses algorithms to automatically locate the complex patterns and relationships in learner data including demographic characteristics, behavior logs and interaction metrics recorded by learning management systems (LMSs) [46]. Due to its predictive nature, it lends well to early intervention of children at risk of failing or excelling, with sorting students into performance groups and optimal adaptive learning

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

paths [47]. Some ML methods provide better predictive validity in educational research. e.g., Random Forest (RF) and Gradient Boosting Machines (GBM) are known to perform better than the traditional regression in predicting student dropout and course completion rates [48]. Deep models such as CNNs and LSTMs have been used to model temporal dynamics of student engagement and learning trajectories [49]. Also, Support Vector Machines (SVM's) have already been employed for binary classification problems such as pass/fail prediction with promising accuracy [50]. Further evidence that behavioral and clickstream data are becoming integrated with ML frameworks is provided by recent research. Through studying variables such as login-success, time-on-task and resource-access usage, researchers have obtained predictive accuracies higher than 90% for the students under risk [51]. In addition, interpretable ML methods are emerging that enable educators to understand the outputs of algorithms and integrate predictions with pedagogical decision making [52]. Yet ML methods have not been implemented without difficulty in educational settings. Foremost among these there is the "black box" character of a large number of algorithms, which hampers interpretability by policy makers and educators [53]. Moreover over fitting and data imbalance are also challenges in the application of ML to various student populations [54]. These constraints highlight the value of combining ML with theory-driven approaches like SEM to reconcile predictive with conceptual clarity. The utilization of machine learning in education serves several purposes such as early warning student dropout, adapting pathways for students, improving the accuracy of prediction and classifying learners. Figure 2 the fundamental responsibilities of machine learning in education are summarized in this figure with a particular emphasis on data analysis, prediction and personalization.

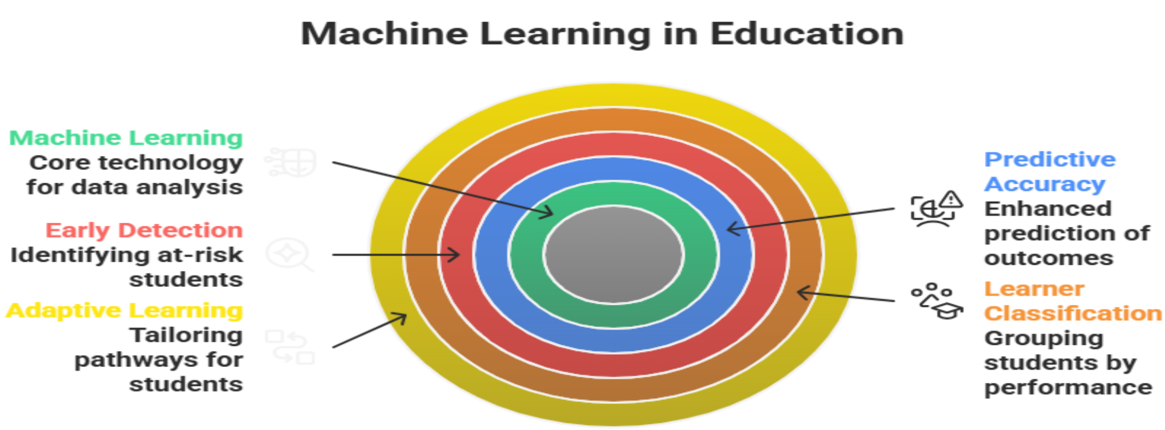

Figure 2. Machine learning in education: Essential applications like early warning system for at-risk students, adaptive tutoring systems, accuracy prediction and learner's profiling.

3.3 Hybrid SEM–ML Approaches

The combination of SEM and ML has been identified as a promising direction in educational research, for it can capitalize on the benefits of theory-driven and data-driven approaches. That is,

International Journal of Applied Mathematics

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

SEM ensures conceptual clarification and latencies' construct validation; ML adds predictive precision and allows for the identification of non-linear relationships. As a result, hybrid SEM–ML frameworks provide an equilibrium approach for balanced exploration and prediction of educational outcomes [55].

However, there are studies showing that in higher education the hybrid approaches hold the promise. As an example, SEM has been employed to estimate theoretical links between constructs (e.g., motivation, satisfaction and readiness), and then the estimated latent variables are taken as input of ML algorithms (i.e., Random Forests or Gradient Boosting) in performance prediction [56]. Likewise, combining SEM with deep learning improved predictive accuracy for at-risk learners and also enhanced interpretability using proposed constructs from the SEM [57]. Hybrid SEM–ML models have been also employed in the Middle East and the developing world, questioning theoretical concepts related to LMS adoption by bridging students' perceptions of an LMS with their actual usage (behavior) [58]. Moreover, the use of explainable AI (XAI) SHAP and LIME methods to enhance transparency could help policy-makers and educators better understand how predictors affect academic results [59]. However, while highly beneficial, there are still barriers in the deployment of these hybrid SEM–ML models. These include: complexity of computation, large number of training data and the incapacity to recognize smaller part of objects based on country-specific properties (robustness), as well lack of localized studies in transition-based higher education systems like Iraq [60]. These gaps need to be filled by developing contextually grounded frameworks that strike a balance of sound theoretical base, good predictive properties and interpretability. Figure 3 illustrates the hybrid SEM–ML model, in which SEM validates theory constructs, ML captures non-linear relationships, deep learning promotes early risk detection and interpretability of models prediction is supported by XAI.

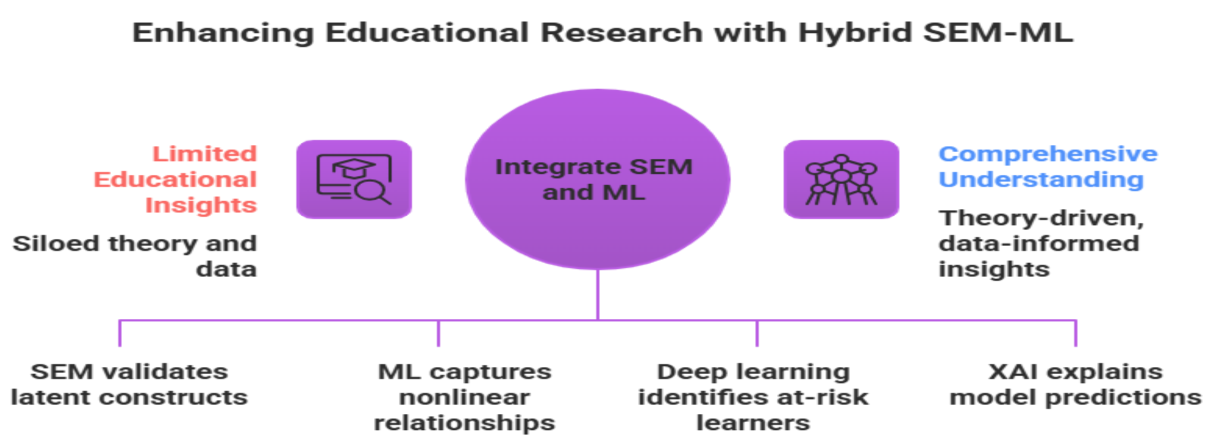

Figure 3. Hybrid SEM (structural equation model)–based ML framework in education for integrated scenario, integrating SEM concepts with ML predictive analysis and marrying deep learning for risk detection along with XAI for explain ability

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

4. Comparative Analysis: SEM vs ML vs Hybrid SEM–ML

4.1 Evaluation Dimensions

In order to compare the SEM, ML, and hybrid SEM–ML approaches in the present review we consider: (i) construct validity and theoretical fit; (ii) predictive performance (e.g., accuracy, F1 measure, AUC); (iii) interpretability and action ability; (iv) data-requirements and scalability; as well as (v) contextual adaptability of under-resourced environments such as Indian higher education [61,62].

4.2 Structural Equation Modeling (SEM)

For example, a strength of SEM is in theory validation and system reliability. Reliability (Cronbach's $\alpha > 0.80$) and validity estimates were acceptable, and the model fits supported good explanation as to how motivation, engagement, satisfaction, usability and readiness impact outcomes [63, 64]. Nevertheless, the prediction power of SEM is generally moderate to weak under nonlinear relations or existence of high-dimension LMS traces, thus leading early-warning applications without supporting models [65].

4.3 Machine Learning (ML)

ML methods (such as RF/GBM/SVM/DL) often yield better predictive accuracy than SEM baselines, particularly when we integrate clickstream variables such as time-on-task, session frequency and resource transitions [66,67]. This potential is also shared by early identification of at-risk learners and adaptive pathway suggestion [68]. Notable limitations of this technique include its opacity (black-box methodology), potential bias, and susceptibility to class skewing that may undermine trust in the predictions together with adoption downstream by educators and policy makers [69].

4.4 Hybrid SEM–ML

Hybrid methods utilize SEM-validated latent constructs as structured, theory-supported features to ML learners typically showing better results for both AUC/F1 and interpretability than the standalone approaches [70,71]. Addition of XAI (e.g., SHAP, LIME) also enhances interpretability of factor contributions (eg, marginal effectiveness of engagement vs readiness), and enabling policy translation in resource-determined setting [72]. For cases like Iraq, hybrids are prom using as they preserve the conceptual rigor as demanded by stakeholders and yet provide predictive power for early interventions.

4.5 Practical Takeaways

In application, SEM is more efficient for examining theoretical models, verifying measuring instruments and testing mediation/moderation mediating effects among perception constructs and ML has its advantage to prediction scenarios – early warning events and classification using big

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

data samples with lots of diversities from it. This hybrid SEM–ML method offers a superior trade-off by relying on an integration of the theory-justified constructs from SEM and the prediction capabilities of ML, which is further supported through explainable AI tools to enable both strong conceptual validation as well as high-accuracy decision-making that can be directly acted upon in educational settings [70–72]. To ensure a clear comparison, Table 2 outlines the features of SEM, ML and Hybrid (SEM–ML) approaches from different evaluation dimensions (objectives of these approaches, common inputs for SEM/ML/Hybrid (SEM–ML), advantages and disadvantages) as well as suggested best scenarios to use them and their used performance measures

Table 2 Comparative analysis of (SEM, ML, Hybrid SEM–ML).

Method	Primary Goal	Typical Inputs	Strengths	Limitations	Best Use Cases	Example Metrics	Key References (2020–2025)
SEM	Theory testing & validation	Survey-based latent constructs (motivation, engagement, satisfaction, readiness)	High construct validity; strong mediation/moderation testing; robust model fit indices	Limited predictive power; weak with nonlinear or high-dimensional LMS data	Validating perception-based models; evaluating readiness/satisfaction	Reliability (α > 0.80), AVE > 0.50, CFI/TLI > 0.90	[40], [41], [42], [43], [63], [64].
ML	Prediction & classification	Behavioral LMS logs, clickstream data, demographics	High predictive accuracy; handles nonlinear & high-dimensional data; supports early interventions	"Black-box" interpretability issues; bias risk; overfitting; class imbalance	Dropout prediction; early-warning systems; adaptive/personalized learning	Accuracy > 90%, F1 > 0.85, AUC-ROC > 0.90	[46], [47], [48], [49], [50], [52], [54].
Hybrid SEM–ML	Balanced explanation &	SEM-derived latent constructs	Combines theory validation with predictive	Computational complexity; large	Transitional higher education contexts;	Improved AUC/F1 compared to SEM	[55], [56], [57], [58],

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

	predictio n	+ LMS log data	accuracy; XAI (SHAP/LIME) enhances interpretability	dataset requireme nts; limited localized studies (Iraq/ME NA)	policy-driven analytics; interpretable prediction models	or ML alone; interpreta ble SHAP/LI ME outputs	[59], [60], [83].

Table 2 summarizes the pros and cons of SEM, ML and hybrid SEM–ML methods. SEM has high levels of construct validity and it is grounded in theory, but less predictive power when dealing with complex non-linear settings. On the other hand, ML enjoys better prediction accuracy and scalability using large-scale behavioral data but at the cost of interpretability due to its black-box nature. The SEM–ML hybrid approach is thus a methodological integration between the explanation power of SEM and the predictive accuracy gained from ML, supported by explainable AI methods such as SHAP and LIME, which is particularly meaningful within transitioning higher education systems where both theoretical alignment and actionable prediction would be needed [70–72].

5. Research Gaps and Conceptual Justification

5.1 Research Gaps

While SEM and ML have each in turn progressed the investigation on e-learning outcomes, there are still few gaps. First, the majority of SEM-based studies are concentrated on reinforcing perception constructs (motivation, satisfaction, engagement and readiness) only and they hardly reach the level of PM for EWS [73]. Second, despite ML models reaching high predictive accuracy rates in particular when used with behavioral user data from LMS and clickstream analytics, it generally suffers from a lack of theoretical grounding and interpretability that diminish the suitability for policy making [74]. Third, the field of hybrid SEM–ML models is relatively new and there are only a few empirical applications published recently with most being focused in technological advanced areas (e.g., North America or Europe) which ignores developing and transitional country contexts [75]. Fourth, research in Iraq and broader MENA region is still limited despite significant challenges in e-learning adoption throughout and post the COVID-19 pandemic [76]. Last, but not least, explainable AI (XAI) tools like SHAP or LIME have just recently found their way into education research and an adaptation for SEM–ML frameworks as local evaluation methods is at most missing in local studies [77].

5.2 Conceptual Justification

It is against this backdrop that the current study introduces a context-sensitive hybrid SEM–ML model for Iraqi HEIs. I develop this framework to take advantage of SEM's capabilities in

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

validating perception constructs (perceptual measurement model) and ML's ability for prediction, but also integrate XAI to ensure interpretation and policy relevance. By integrating survey-based constructs (motivation, engagement, satisfaction, usability and readiness) with AG LMS log behavioral variables the model seeks to fill the current disconnect between theory-driven and data driven approaches [57]. The fact that such an amalgamation not just predicts well, but also offers insights for Iraqi educators, administrators and policy makers is necessary as digital readiness of country along with infrastructure and institutional capacity are poor [79]. Finally, situating the study within the wider MENA context allows for comparison across regions and increases the relevance of this work beyond Iraq to global debates around how best to reconcile theory, prediction and transparency in digital education systems [80]. At this point the identified research gaps and proposed contributions are summarized in Figure 4 which shows how the SEM, ML, hybrid approach limitations can be addressed through the proposed SEM–ML framework with XAI.

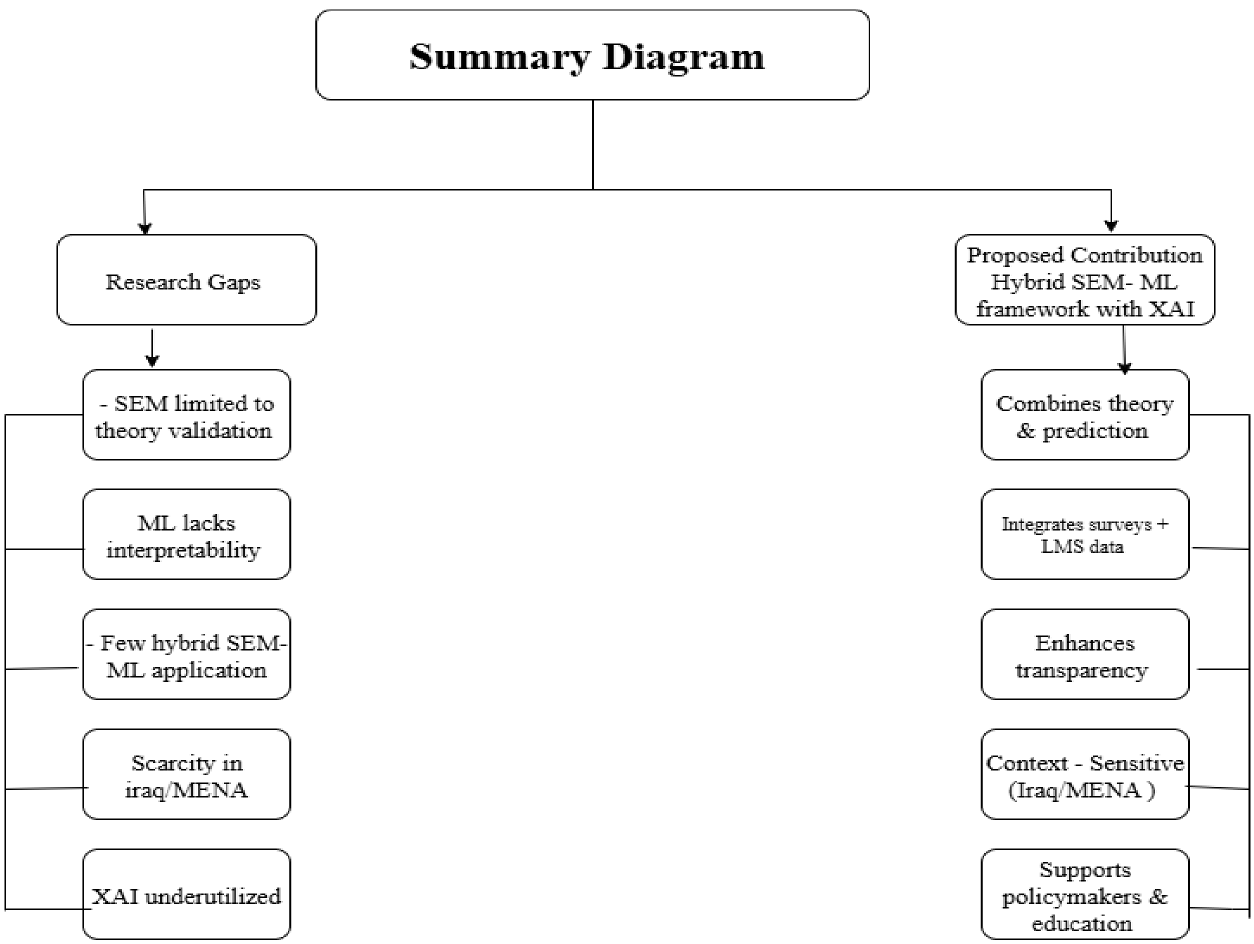

Figure 4. Summary diagram of research gaps and proposed contribution.

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

In order to summarize the results of this review a final conceptual framework is shown in Figure 5. The model combines learner perceived constructs and their behavior in the LMS through hybrid SEM -ML pipeline, assisted by XAI for interpretability, customized for Iraqi/MENA higher education.

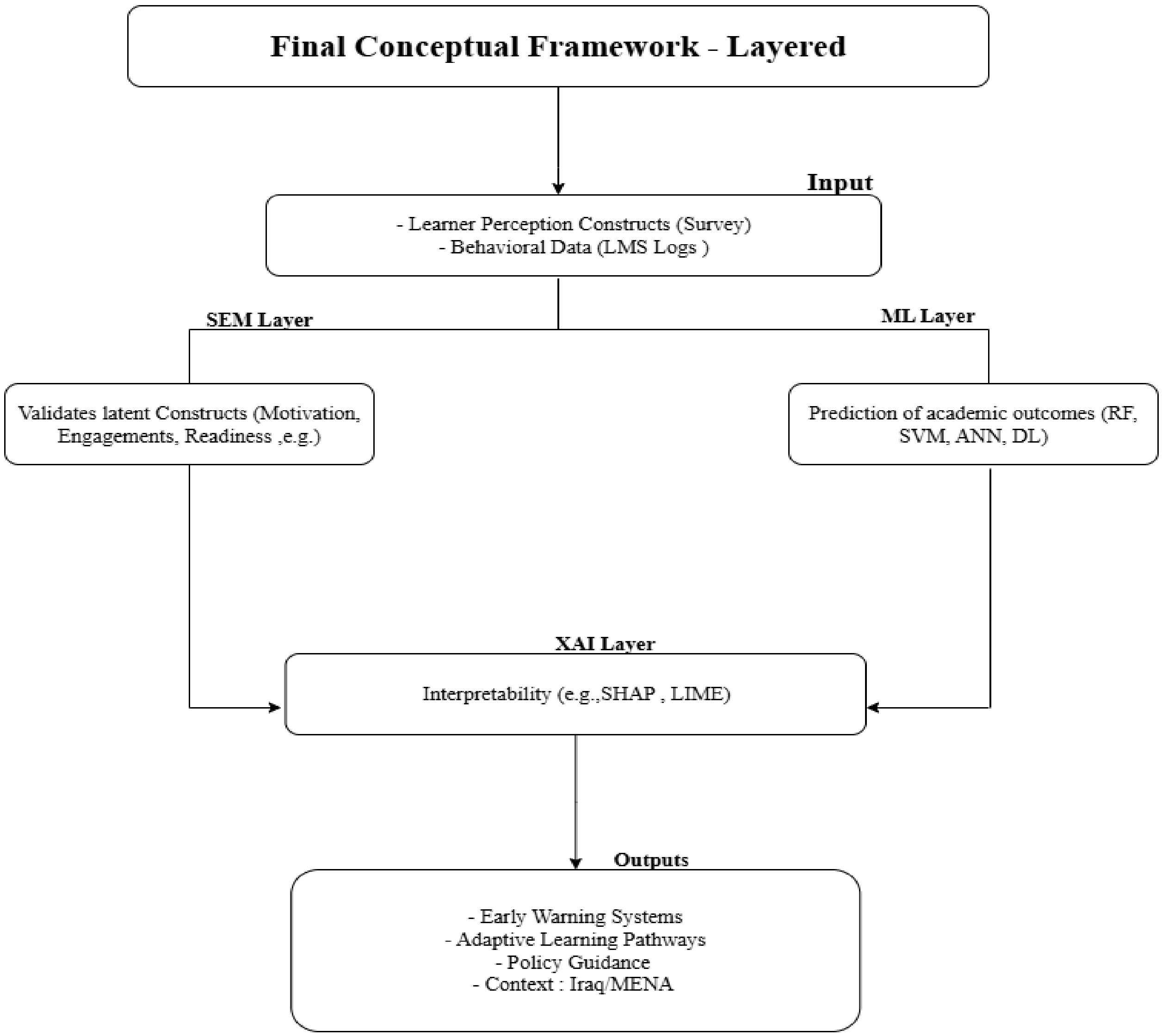

Figure 5. Final conceptual framework of the proposed hybrid SEM–ML model with XAI in Iraqi HE for academic performance prediction.

6. Discussion

6.1 Theoretical Implications

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Such review has highlighted that SEM and ML should not be seen as competing but, rather, as complementary in the further drive of e-learning. SEM is important in confirming motives, engagement and satisfaction readiness constructs have the required psychometric value when examining models [81]. But its explanatory emphasis is not able to account for non-linear and dynamic patterns same as the behavior data from LMS environments. On the other hand, ML attains excellent predictive power by mining relationships in large-scale and multidimensional datasets but lacks conceptual structure behind it [82]. The combination of SEM and an ML approach mediated by variables provides a solution to these tensions by embedding established constructs within ML models, leading to theoretically cohesive and empirically robust findings [83]. This integration is actually a major theoretical contribution as the two perspectives have remained at odds for some time.

6.2 Practical Implications

Practically speaking, combining SEM with ML has meaningful applications across higher education. By using ML algorithms to predict students at risk and personalized learning paths, instructors are able to make timely interventions [84]. When based on SEM-validated constructs, these predictions become actionable and tie outcomes to interpretable factors such as readiness or engagement. Additionally, the involvement of explainable AI (XAI) methods including SHAP [86] and LIME provides transparency and advances trust for educators and policy makers [85]. Such hybrid models can contribute to data-based decision-making and resource allocation in young civil institutions in Iraq and MENA region where infrastructural impediments as well as readiness difficulties remain [86].

6.3 Regional Significance

The outcomes of this review are particularly important for Iraq and similar emerging education systems. Although global research studies on SEM–ML integration exist in developed contexts, localized research is limited [87]. The higher education sector in Iraq is confronted with special challenges, such as the fragility of the internet and inconsistency related to LMS adoption, and varies from one faculty member to another regarding digital skills. A context-sensitive application of SEM–ML could have a twofold impact: it might help keep theoretical precision while assessing students' perceptions, and offer practical knowledge for policy-makers at the institutional level [88]. The study locates this work within local as well as regional framings, and in so doing addresses the specifics of the challenges facing Iraq while also feeding into wider comparative debates in global literature.

6.4 Limitations

While the integration of SEM and ML presents promising opportunities, several limitations must be acknowledged. First, hybrid models typically require large and diverse datasets to achieve stable

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ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

performance, yet many Iraqi higher education institutions lack sufficient data infrastructure. Second, although ML algorithms deliver high predictive accuracy, their computational complexity can be a barrier in resource-constrained environments. Third, most existing SEM–ML studies are cross-sectional, limiting their generalizability and failing to capture long-term dynamics in student performance. Fourth, although explainable AI (XAI) techniques such as SHAP and LIME offer interpretability, their application in educational contexts remains in its early stages, raising questions about usability for non-technical stakeholders such as educators and policymakers. Finally, a notable publication bias exists: the majority of SEM–ML research has been conducted in developed regions (e.g., North America, Europe, and parts of Asia), with far fewer studies emerging from Iraq and the wider MENA region. This geographic imbalance restricts the evidence base available to inform policy and practice in under-resourced settings, underscoring the urgent need for more localized and context-sensitive investigations [91].

7. Conclusion

This review examined the role of Structural Equation Modeling (SEM), Machine Learning (ML), and their hybrid integration in predicting and understanding academic outcomes in e-learning environments. SEM provides strong construct validation and theoretical grounding, while ML contributes superior predictive power for complex and nonlinear data. A hybrid SEM–ML approach, particularly when enhanced with explainable AI (XAI) tools such as SHAP and LIME, offers a balanced framework that combines interpretability with predictive accuracy.

For Iraq and the wider MENA region, where digital infrastructure, institutional readiness, and policy coherence remain limited, adopting hybrid SEM–ML frameworks is both a necessity and an opportunity. These models can provide transparent, evidence-based tools for early risk detection, personalized learning pathways, and effective resource allocation.

Future directions should focus on three priorities. First, investment in educational data infrastructure is essential to support large-scale and reliable SEM–ML applications. Second, capacity building in SEM, ML, and XAI methods among faculty and researchers will enhance local expertise and sustainability. Third, longitudinal and context-specific studies are needed to strengthen predictive stability and ensure that outcomes are meaningful for Iraqi higher education policy and practice. By addressing these priorities, hybrid SEM–ML frameworks can move from theoretical promise to practical impact, advancing both the quality and equity of digital education in transitional and under-resourced contexts.

Funding:

This research received no external funding.

Conflict of Interest:

The authors declare no conflict of interest.

Volume 38 No. 9s , 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Acknowledgements:
The authors would like to thank BIOCORE Research Group, Center for Advanced Computing Technology (C-ACT), Fakulti Kecerdasan Buatan dan Keselamatan Siber (FAIX) and Centre for Research and Innovation Management (CRIM), Universiti Teknikal Malaysia Melaka (UTeM) for providing the facilities and support for this research.

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Received: August 08 2025

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