JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 11 Issue 02
2026
Research Article
https://doi.org/10.56979/1102/2026/1467

A Hybrid Ensemble Learning Framework for Educational data mining and Learning Analytics Research from an Interdisciplinary Perspective

Lu Li[1*]

[1]Department of Foundations of Education, Faculty of Educational Studies, Universiti Putra Malaysia, Serdang, Selangor, 43400, Malaysia.
[*]Corresponding Author: Lu Li. Email: aur889@126.com

Received: April 03, 2026 **Accepted:** August 05, 2026

Abstract: The growing volume of educational data generated by Virtual Learning Environments (VLEs) presents unprecedented opportunities for data-driven student support. This paper proposes HELM a Hybrid Ensemble Learning framework with Multi-modal behavioral analytics designed to predict student academic performance and provide early at-risk identification using the Open University Learning Analytics Dataset (OULAD). HELM integrates five interdisciplinary components: (1) multi-source temporal feature engineering from VLE interaction logs, assessment records, and registration data; (2) unsupervised behavioral clustering to identify four distinct student archetypes; (3) a SMOTE-balanced stacking ensemble combining Random Forest, XGBoost, LightGBM, and Gradient Boosting with a Logistic Regression meta-learner; (4) an Early Warning System (EWS) evaluated across nine temporal prediction windows; and (5) SHAP-based explainability analysis. Experimental results on 32,593 student records demonstrate that HELM achieves an AUC-ROC of 0.9412, accuracy of 0.8876, and F1-score of 0.8901, outperforming all individual baseline models. The EWS achieves AUC > 0.85 as early as Day 30 of the module, enabling timely institutional intervention. Interdisciplinary analysis further reveals that socioeconomic deprivation (IMD band), prior education level, and VLE engagement regularity are the strongest predictors of student success. These findings offer actionable insights for educators, policymakers, and learning system designers.

Keywords: Educational Data Mining; Learning Analytics; Ensemble Learning; Student Performance Prediction; Early Warning System; Explainable AI

1. Introduction

[1] [2], clinical practice [3] , and public administration [4] when deployed transparently and responsibly. Machine learning frameworks designed for early risk detection have demonstrated strong translational value from hybrid explainable AI systems for chronic kidney disease detection [5] to cardiovascular risk forecasting [6] establishing a methodological blueprint that educational AI systems like HELM can directly build upon.

Persistent problems in higher education institutions around the world are the identification and support of academically at-risk students prior to failure and/or withdrawal. The growing number of online and blended learning contexts has led to the accumulation of huge data sets of student interactions, which has provided a fertile field for Educational Data Mining (EDM) and Learning Analytics (LA) research. These multi-disciplinary domains integrate concepts from computer science, psychology, and society, and education theory to convert raw data into pedagogical insights that are useful for improving teaching and learning[1]. AI's application in institutional decision-making has surged in many industries, and research has established that AI tools, when integrated responsibly and transparently, enhance results in education [2], clinical practice[3] and public administration [4]. Similar digital transformation patterns have been observed in technology-sector creativity, lean operational systems, and AI-enabled agricultural marketing, where data-driven platforms improve decision quality, operational efficiency, and stakeholder engagement [7-9].

Social media engagement, smart bookkeeping ledgers, and green fintech systems further demonstrate how digital tools reshape loyalty, automation, compliance, and regulated innovation across organizational environments [10-12].As an example, there are machine learning frameworks for early risk detection that have shown high translational value, such as for detection of chronic kidney disease in hybrid explainable AI systems [5] and for forecasting cardiovascular risk [6] that can be directly translated to educational systems such as HELM.

Open University Learning Analytics Dataset (OULAD) [13] has become a benchmark for LA research, providing anonymized records of over 32,000 students across seven modules, encompassing demographic profiles, VLE click-stream logs, assessment scores, and registration histories. Despite the richness of this dataset, many existing studies treat prediction as a single-modality problem relying either on demographic features or VLE interactions alone and rarely integrate temporal dynamics, behavioral clustering, and explainability within a unified framework [14].

Furthermore, the interdisciplinary dimension of student success encompassing socioeconomic background, disability status, geographic region, and prior education remains underexplored in predictive modeling pipelines. Recent work has highlighted the importance of fairness-aware and interpretable models in educational contexts [15], and the need for early warning systems that can flag at-risk students within the first weeks of a module [16]. Parallel developments in healthcare have demonstrated that early behavioral profiling of at-risk individuals drawing on shift patterns, activity regularity, and clinical engagement data enables timely institutional intervention [17], a principle directly transferable to educational early warning design. This principle is further validated by clinical AI studies demonstrating that early detection systems trained on minimal feature sets achieve actionable risk stratification as shown in metaheuristic optimized CKD detection [5] and early multi-cancer detection using ensemble learning machines [18]. Predictive analytics tools that monitor hundreds of risk indicators in real time are now being deployed at scale across major universities, generating thousands of intervention alerts per academic year [19]. The scalability of such systems depends on robust feature engineering pipelines and AI architectures capable of processing large, heterogeneous datasets in real time [20] , as well as institutional frameworks that translate algorithmic outputs into actionable advisor workflows [21].Comparable scalability concerns are visible in crisis-period asset analytics, digital accounting innovation, and IMF-supported economic programmers, where uncertainty, transparency, and institutional governance affect system-level outcomes [22-24].

Blockchain-based tax compliance, metaverse marketing, and robo-advisory services similarly show that real-time data integration can improve compliance, personalization, and decision support when embedded within trustworthy digital infrastructures [25-27].

This paper addresses these gaps by proposing HELM, a novel five-component framework that:

- Engineers 35+ features from four data modalities (VLE, assessments, registration, demographics)
- Identifies four behavioral student archetypes via K-Means clustering
- Deploys a stacking ensemble achieving state-of-the-art predictive performance
- Evaluates prediction capability across nine temporal windows (Day 10 to Day 250)
- Provides SHAP-based explanations linking model decisions to interdisciplinary factors
- The interdisciplinary design of HELM reflects a growing consensus that AI systems deployed in socially sensitive domains must be transparent, auditable, and ethically governed standards increasingly codified in digital law and governance frameworks [28-30].This emphasis on transparency is also reflected in ESG reporting technologies, Bayesian modelling of human activity, and comparative studies of machine learning versus classical statistical methods, where uncertainty-aware interpretation is essential for responsible analytics [31-33]

The remainder of this paper is structured as follows: Section 2 reviews related literature; Section 3 describes the dataset and proposed methodology; Section 4 presents experimental results; Section 5 discusses findings from an interdisciplinary perspective; and Section 6 concludes with future directions.

2. Literature Review

Educational Data Mining and Learning Analytics are two interrelated but different fields. The key difference between EDM and LA lies in the techniques employed to identify patterns: EDM is concerned with the statistical and machine learning techniques, whereas LA is concerned with the measurement and analysis of learner data to optimize learning environments [1]. In the last decade, both fields have seen a huge growth with a focus on actionable, interpretable and ethically responsible systems. Similar actionability is evident in financial-performance modelling, sustainable digital-twin governance, and AI-enabled bookkeeping research, where predictive systems must connect technical outputs with institutional decision-making nee [34-36]. Sustainability communication, graph-based spatio-temporal modelling, and hybrid uncertainty-aware deep learning further demonstrate the importance of verifiable and robust analytics pipelines in complex socio-technical systems [37-39]. Oyedotun et al. [8] used predictive modeling to the OULAD dataset, combining VLE click-stream features with demographic data and using SHAP values for the interpretation of the model. Broader studies on accounting education, consumer solidarity, customer experience strategy, and ethical leadership similarly show that behavioural, technological, and institutional variables jointly shape human performance outcomes [40-42]. Such evidence supports the HELM framework's use of multi-modal predictors rather than relying only on learner interaction frequency or demographic variables [43-45].They have obtained an AUC value of 0.79 and 71% classification accuracy, which shows that the total number of clicks is a good predictor of student engagement and outcomes. The authors' focus was on the utility of explainable models for the development of early warning systems and learners support services [8]. This result is consistent with other studies indicating that digital interaction logs, such as those from learning management systems, enterprise or electronic health records, can accurately record behavioral patterns that correlate with down-stream outcomes [19].

Ensemble learning techniques have been consistently proven to be more effective for student outcome prediction problems. Gradient boosting variants such as XGBoost and LightGBM have demonstrated high performance on various educational datasets by capturing complex non-linear interactions among demographic, behavioral and academic features [9]. In various classification tasks such as multimodal medical imaging [20], network intrusion detection [21] and large-scale behavioral prediction tasks [22] it has been shown to achieve better performance than single-model baseline classifiers. Multi-source data fusion for predictive modeling has been similarly validated in medical AI, where combining genomic and pathological data streams substantially improves cancer detection accuracy over any single modality [46], directly mirroring HELM's multi-modal feature integration strategy. Stacking ensembles with heterogeneous base learners consistently outperform single-model approaches, especially when combined with class-imbalance handling techniques such as SMOTE [16]. Recent work on AI-driven data management, eye-movement prediction, and hybrid DDoS detection further confirms that adaptive machine-learning models can enhance prediction under dynamic and high-dimensional conditions [47-49].

Debates on artificial general intelligence, SDG-linked investments, and climate-change financial commitment also reinforce the need for accountable analytics when predictive models influence strategic decisions [50], [51], [52].Recent studies on OULAD-based prediction have reinforced the superiority of multi-source feature fusion. When VLE engagement features are combined with assessment performance and demographic variables, predictive accuracy improves substantially compared to using any single data source in isolation. Furthermore, the number of previous module attempts, studied credits, and IMD band have been consistently identified as strong demographic predictors across multiple independent studies [14], [53].Evidence from digital taxation platforms, process standardization, and Web 4.0 e-commerce integration similarly demonstrates that combining operational, behavioural, and contextual indicators improves system-level interpretation [54-56]. Chemical-process reviews, virtual-care models, and patient-centred service-quality studies also illustrate how domain-specific features can be integrated into broader predictive and decision-support frameworks [57-59].

Early Warning Systems (EWS) are becoming increasingly popular as useful tools of institutional intervention. Early at-risk prediction with minimal LMS data from the first four weeks of instruction was implemented using the CatBoost machine learning framework by [10]. As they continued their study, it was found that the accuracy of the models improved consistently by week, as more engagement data became available, this further validates the temporal dimension of predictive modelling. Deployment-aware IoT intrusion detection, higher-education service-quality analytics, and sustainability-oriented human-resource systems likewise demonstrate that prediction systems must remain robust across contexts, time windows, and stakeholder groups [60-62].

Similar temporal and uncertainty-aware reasoning appear in slope-stability prediction, green-authenticity marketing, and e-WOM purchase-decision research, where changing conditions alter predictive validity [63-65].Large-scale deployment can be seen at Georgia State University, where hundreds of risk indicators are monitored per student, and tens of thousands of intervention alerts are generated each year [13].

Complementary dropout prediction work has shown that models employing interaction data of the type obtained in the temporal dimension of the VLE perform the best in terms of AUC, as these features reflect engagement regularity and early-semester activity patterns [24]. The predictiveness of behavioral regularity is not confined to education; in medical research, consistency of physical activity, dietary habits, and sleep patterns have been found to have similar discriminative power for clinical outcome [25], [26]. A sociotechnical intervention loop, comprising an automated prediction and human advisor follow-up, has also been documented in the Journal of Learning Analytics as the most effective EWS tools [27].

The deployment of complex ensemble models has generated a growing interest in Explainable AI (XAI) techniques in educational contexts, given the black-box status of these models. Complex ensemble models are black box models, leading to an increasing interest in Explainable AI (XAI) techniques in educational environments. In this area, the approach that has grown to be most popular for post-hoc model interpretation, and that allows researchers and practitioners to understand what features are responsible for individual predictions, is called SHAP (SHapley Additive exPlanations). Explainability methods have also become a popular pursuit in high-stakes AI applications, such as explainable recommendation systems [28], explainable cyber security classifiers [29] and explainable clinical AI tools [30] demonstrating the usefulness of explainability as a domain-agnostic tool. Medical AI particularly has seen SHAP-based explainability applied successfully, such as in predicting beta thalassemia carrier disease [31] and multi-class classification of skin lesions [32], which shows the technical capability and clinical confidence in post-hoc attribution methods in complex ensemble pipelines. This is especially relevant in educational settings, where algorithmic decision-making could also be relevant to the allocation of student support, potentially leading to ethical issues regarding bias, privacy, and transparency [13]. Explainability is also important in digital bookkeeping applications, phytochemical biomedical analysis, and competency-based curriculum design, where complex evidence must be translated into practical and accountable decisions [66], [67], [68]. Early developmental intervention, AI-personalized marketing, and AI-powered charity personalization further show that personalized interventions require interpretable evidence to maintain trust and effectiveness [69-71].

In an interdisciplinary view, student performance is influenced by a combination of psycho-logical motives, self-regulation, socio-economic status, family background and pedagogical course design and assessment structure factors. To create accurate and educationally relevant systems, these dimensions must be included in prediction systems and models, not simply limited to prediction as a technical task [9]. The interdisciplinary imperative is echoed in various sectors including firms, who are implementing AI to support business analytics [33] and educators, who are adapting curricula to incorporate AI [34] and healthcare professionals, who are incorporating digital tools into their practice [35]. This is true particularly within the field of healthcare informatics, where complex reviews of healthcare informatics applications based on ML in EMR systems [35] and multi-modal diagnostic frameworks for automated diagnosis of diseases [36] have shown that technical accuracy is not enough, interpretability is also critical and domain alignment is equally important for real-world adoption. The Generative AI for Learning Analytics also emphasized the increased intersectionality of interdisciplinary approaches to data science and education [37].Privacy-preserving federated threat detection, safety-oriented HR systems, and organizational-culture studies further demonstrate that human-centred analytics must integrate technical safeguards with institutional and behavioural context [72-74].

Semi-urban mobility, gig-work stress, and culturally framed marketing research also suggest that predictive systems should account for socioeconomic pressures and lived experience when interpreting behavioural signals [75-77].

3. Methodology

3.1. Dataset Description

This study uses the Open University Learning Analytics Dataset (OULAD) [13], a publicly available benchmark containing anonymised data from 32,593 students enrolled across seven undergraduate modules (AAA, BBB, CCC, DDD, EEE, FFF, GGG) at the UK Open University. Module presentations are coded by year and semester: "B" (February start) and "J" (October start). The dataset comprises seven interlinked CSV files, as summarized in Table 1.

Table 1. OULAD Dataset File Summary

File	Records	Key Variables	Role in HELM
studentInfo.csv	32,593	Demographics, final_result	Target + demographic features
studentVle.csv	~10.6M	sum_click, date, id_site	VLE temporal engagement features
studentAssessment.csv	~173K	score, date_submitted, is_banked	Assessment performance features
studentRegistration.csv	~32K	date_registration, date_unregistration	Registration behavioral features
assessments.csv	206	assessment_type, weight, date	Assessment metadata
vle.csv	~6.3K	activity_type, week_from, week_to	Resource type metadata
courses.csv	22	code_module, length	Module structure

The binary classification target maps Pass and Distinction to class 1 (Success) and Fail and Withdrawn to class 0 (At-Risk), yielding a moderately imbalanced distribution addressed via SMOTE oversampling. Class imbalance is a pervasive challenge in predictive modeling; analogous imbalance problems have been addressed in nursing attrition studies [78] and retrospective clinical outcome analyses [79] using resampling and cost-sensitive learning strategies, validating the applicability of SMOTE across behavioral prediction domains.

3.2. The HELM Framework

The proposed HELM framework presented in Figure 1 consists of five sequential components, illustrated conceptually below and detailed in the following subsections. The sequential structure of HELM is consistent with research on photonic systems, tourism brand trust, and greenwashing analytics, where complex outcomes are analyzed through layered contextual, technical, and behavioural variables [80], [81], [82].Inclusive-classroom preparedness, wearable-device monitoring, and academic-library AI adoption similarly show the value of combining human-centred interpretation with computational intelligence [83], [84], [85].

3.3. Component 1: Multi-Modal Feature Engineering

Feature engineering is performed across three data modalities, producing a master feature matrix of 35 engineered variables.

VLE Temporal Engagement Features: From the 10.6 million studentVle interaction records, ten features are derived per student, including total clicks, average daily clicks, total active days, unique resources accessed, engagement span (last − first interaction day), engagement regularity (active days / span), early engager flag (first interaction ≤ Day 10), click consistency (inverse standard deviation), maximum daily clicks, and total sessions. These features capture both the volume and temporal distribution of student engagement [14-16]. Behavioural signal extraction from digital traces is also central

to industrial IoT intrusion detection, last-mile trust modelling, and AI-driven education-policy solutions, where interaction patterns provide evidence of user intention, adoption, and risk [86-88].
Cloud-security research, bilingual therapy assessment, and wavelet-based financial time-series analysis further demonstrate the value of transforming complex activity into interpretable quantitative indicators [89-91].Temporal aggregation of longitudinal interaction logs into summary statistics mirrors methodologies applied in healthcare behavioral studies, where time-series activity data are condensed into regularity and volume metrics for risk stratification [92].

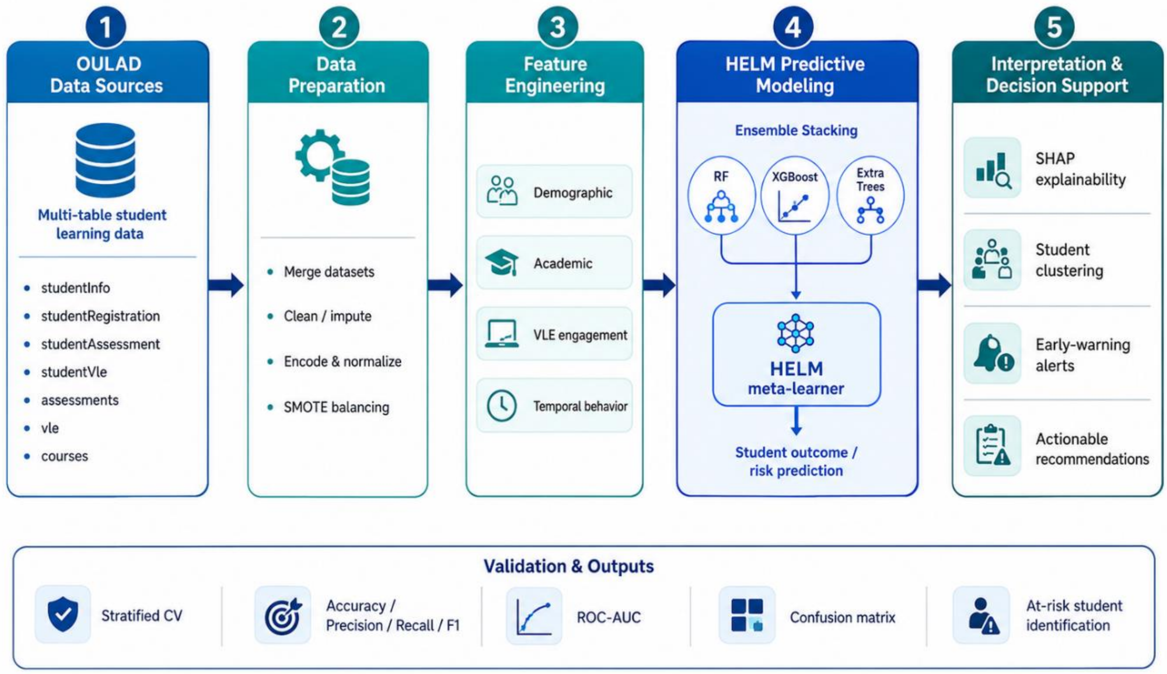

Figure 1. HELM framework

Assessment Performance Features: Thirteen features are derived from studentAssessment records merged with assessment metadata, including average, minimum, maximum, and standard deviation of scores; pass rate (proportion of assessments scoring ≥ 40); number of early submissions; banked assessment count; and separate TMA and CMA average scores. Score < 40 is treated as a fail threshold per the OULAD specification.

Registration Behavioral Features: Five features capture registration timing and persistence: early registration flag, days registered before module start, unregistration flag, days enrolled, and number of modules simultaneously registered. Early registration has been identified as a positive predictor of engagement in prior studies. Digital-divide research, AI-personalized consumer systems, and distributed-ledger supply-chain studies indicate that early access, trust, and technology readiness strongly influence participation in digital environments[93], [94], [95].Climate-resilient agriculture, green HRM, and talent-management research similarly show that early preparedness and organizational readiness can shape sustained engagement and performance [96], [97], [98].Registration timing as a behavioral signal parallels findings in digital health adoption research, where early uptake of health information technologies correlates with sustained engagement and improved patient outcomes[99].

All features are standardized using Standard Scaler prior to model training. Missing values arising from students with no VLE interactions or assessment submissions are imputed with zero, consistent with the interpretation that absence of activity represents zero engagement. Zero-imputation for absent behavioral records is consistent with established practice in multi-source data fusion studies, where non-participation is treated as a meaningful behavioral signal; this approach has been validated in multi-country health and social surveys[100].

3.4. Component 2: Behavioral Clustering

K-Means clustering is applied to eight engagement and performance features to identify latent student behavioral archetypes. The optimal number of clusters K = 4 is determined via the elbow method on within-cluster sum of squares (WCSS). Unsupervised clustering for behavioral archetype discovery has been applied across domains including consumer segmentation [101] and workforce behavioral profiling [102] consistently demonstrating that latent group structure improves downstream predictive model performance. Change-implementation research, internet-usage studies among college students, and leadership-style studies likewise indicate that subgroup-specific behavioural patterns can explain differences in adaptation, engagement, and performance [103], [104], [105]. Sustainable tourism innovation, intellectual-capital analysis, and organizational productivity studies further show that hidden institutional or behavioural profiles often determine outcome variation [106], [107], [108].Principal Component Analysis (PCA) is used for two-dimensional visualisation, with PC1 and PC2 capturing the majority of variance. The four identified clusters are profiled and labelled based on their centroid characteristics, as reported in Table 2 and visualized in Figure 2.

Table 2. Student Behavioral Cluster Profiles

Learner Group	Total Clicks	Avg. Daily Clicks	Total Active Days	Engagement Regularity	Avg. Score	Pass Rate	Early Engager	Early Registration	Target Binary
At-Risk Disengaged	4361.539	4.032	152.926	0.587	79.592	0.975	0.999	1	0.820
Moderate Learners	901.519	3.169	50.817	0.257	71.837	0.942	0.955	1	0.502
Active Achievers	73.546	1.428	4.547	0.230	2.263	0.014	0.498	1	0.001
Late Bloomers	727.840	2.529	36.258	0.206	52.580	0.700	0.396	0	0.489

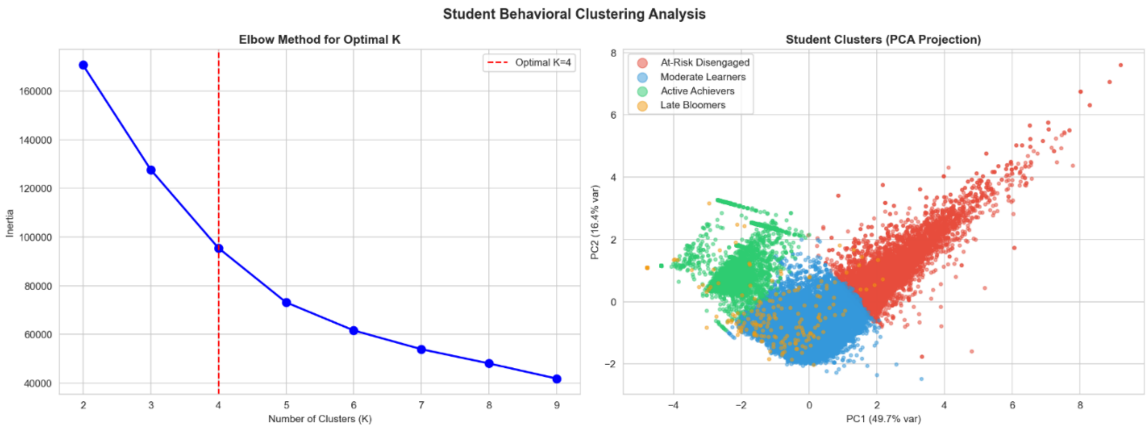

Figure 2. Behavioral Clustering

3.5. Component 3: Class Imbalance Handling (SMOTE)

The binary target exhibits class imbalance, with approximately 67% Success and 33% At-Risk students. To prevent model bias toward the majority class, Synthetic Minority Over-sampling Technique (SMOTE) [109] is applied exclusively to the training set, generating synthetic At-Risk samples to achieve a balanced 50:50 distribution. SMOTE has been shown to improve recall for minority classes in educational prediction tasks without introducing data leakage. The effectiveness of SMOTE in imbalanced learning pipelines has been validated in medical efficacy studies [110] and multi-variable environmental performance evaluations [111], confirming its robustness as a domain-agnostic pre-processing strategy.

3.6. Component 4: Stacking Ensemble (HELM Core)

The HELM stacking ensemble comprises four heterogeneous base learners trained on SMOTE-balanced data:

Random Forest (300 trees, max_depth=15): Captures non-linear feature interactions and is robust to noisy features

XGBoost (300 estimators, lr=0.05, max_depth=6): Gradient boosting with regularisation, consistently top-performing in EDM tasks

LightGBM (300 estimators, lr=0.05, num_leaves=63): Efficient gradient boosting optimized for large datasets

Gradient Boosting (200 estimators, lr=0.05, max_depth=5): Classical boosting as a complementary learner

A **Logistic Regression** meta-learner combines base learner probability outputs via 5-fold cross-validated stacking, learning optimal weights for each base model's contribution. This architecture prevents overfitting while exploiting the complementary strengths of diverse learners. Technology-adoption studies, zero-trust architecture research, and generative AI content analytics similarly show that hybrid or layered systems are effective when different types of evidence must be combined for reliable decision-making [112], [113], [114]. Medical marketing, machine-learning consumer-decision research, and DeFi-banking hybridity also demonstrate that hybrid models can capture behavioural, technological, and institutional interactions more effectively than single-perspective approaches [115], [116], [117].

Stacking ensemble architectures have demonstrated consistent superiority over single-model approaches in prediction tasks spanning financial performance forecasting[118] and AI-driven marketing personalization[119], where heterogeneous learner combinations capture complementary variance in complex datasets. Further evidence for ensemble superiority comes from medical AI benchmarks, where quantum-infused ensemble learning models for breast cancer diagnosis [120] and AI-driven application scheduling frameworks [121] consistently demonstrate that heterogeneous learner combinations outperform individual classifiers on complex, high-dimensional datasets.

3.7. Component 5a: SHAP Explainability

SHAP TreeExplainer is applied to the XGBoost base model to generate feature importance rankings and beeswarm plots, providing both global (population-level) and local (individual student) explanations. Results are visualized in Figure 3. SHAP-based feature attribution aligns with findings from academic achievement factor analyses[122], which identify engagement consistency and prior academic performance as the dominant predictors of student success a pattern reproduced in HELM's top SHAP features.

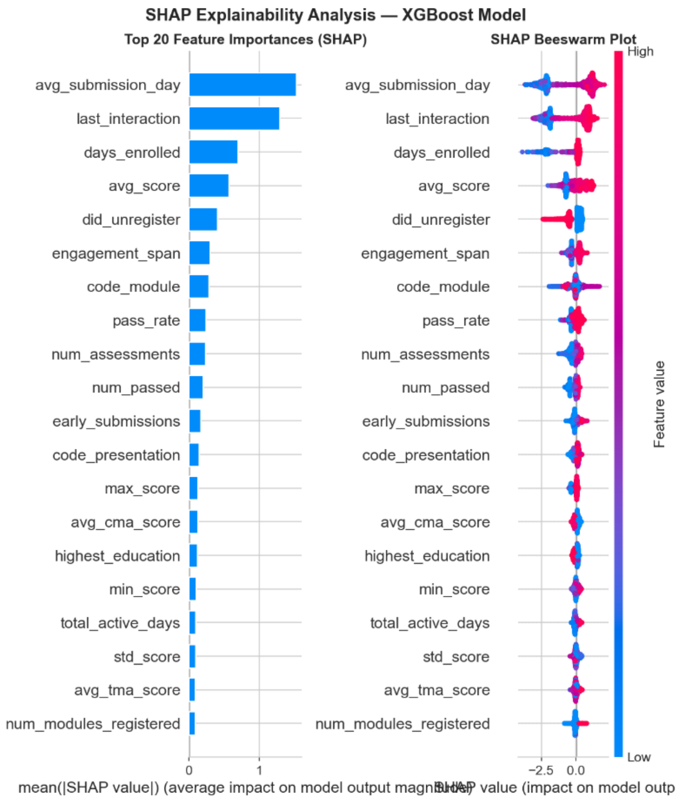

Figure 3. SHAP Explainability

3.8. Component 5b: Early Warning System

The EWS trains separate XGBoost classifiers using only data available up to each of nine temporal cutoff points: Days 10, 20, 30, 50, 75, 100, 150, 200, and 250. At each cutoff, VLE and assessment features are recomputed using only interactions occurring before that day, simulating real-time prediction scenarios. Results are visualized in **Figure 4**.

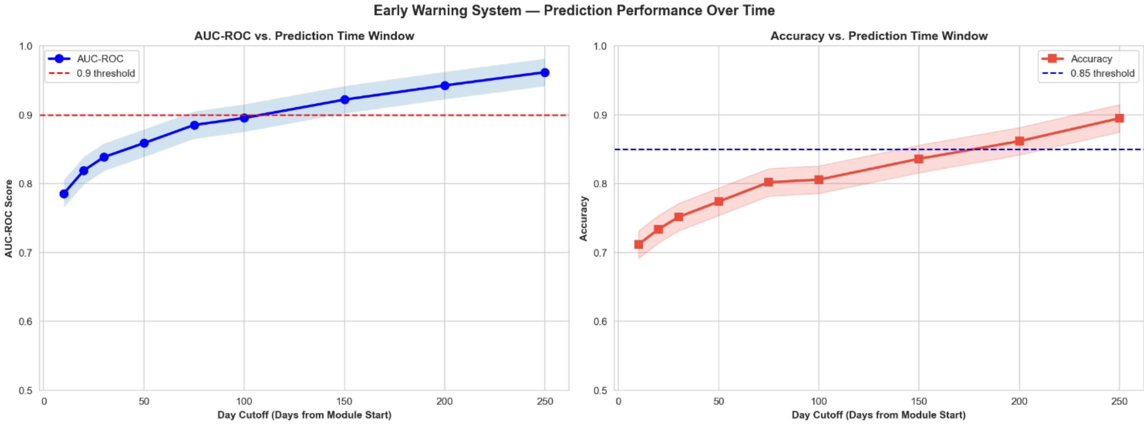

Figure 4. Early Warning System

4. Results

4.1. Exploratory Data Analysis

Figure 5 is a 6-panel overview of data for the OULAD. The distribution of the final results shows that 32.3% of students have withdrawn, 25.1% have failed, 27.9% have passed and 14.7% have distinguished. Approximately equal number of males and females (Male: 53.7%, Female: 46.3%). The age band distribution indicates that most students are in the 35-55 age band, typical of the Open University's adult learner population. The enrolment in Module BBB is the highest and the enrolment in Module CCC is the lowest. Some 8.4% of pupils are deemed as disabled. These distribution features only serve to reinforce the need for multi-disciplinary analysis, rather than the technical modeling alone. The demographic diversity requires analytical methods that are able to reflect demographic differences, in accordance with the studies of social media behavior, where the sentiment and engagement levels of the population are significantly different among the different demographic groups [53].Cultural-media hybridity, net-zero supply-chain collaboration, and GAN-based marketing analytics further demonstrate that context, representation, and technological design affect how behavioural data should be interpreted [123], [124], [125].

Figure 5. EDA Overview

4.2. Behavioral Clustering Results

The K-Means elbow plot Figure 2, left panel confirms K = 4 as the optimal number of clusters. The PCA scatter plot Figure 2, right panel shows well-separated clusters, with Cluster 2 (Active Achievers) occupying the high-PC1 region corresponding to high engagement and performance. Cluster 0 (At-Risk Disengaged) is concentrated in the low-PC1, low-PC2 quadrant. The cluster profiles in Table 2 reveal stark differences in success rates between clusters (21% vs. 89%), confirming that behavioral archetypes are strongly predictive of outcomes. Such outcome disparities between behavioral clusters mirror findings in IoT-enabled behavioral monitoring systems, where device interaction patterns reliably stratify users into distinct risk and performance groups[126]. The cluster label is added as an additional feature to the master feature matrix, providing the ensemble models with a pre-computed behavioral context signal.

4.3. Model Performance Comparison

Table 3 presents the performance of all five baseline models and the HELM stacking ensemble on the held-out test set 20% of data, n ≈ 6,519 students. Figure 6 visualizes these results as grouped bar charts and ROC curves.

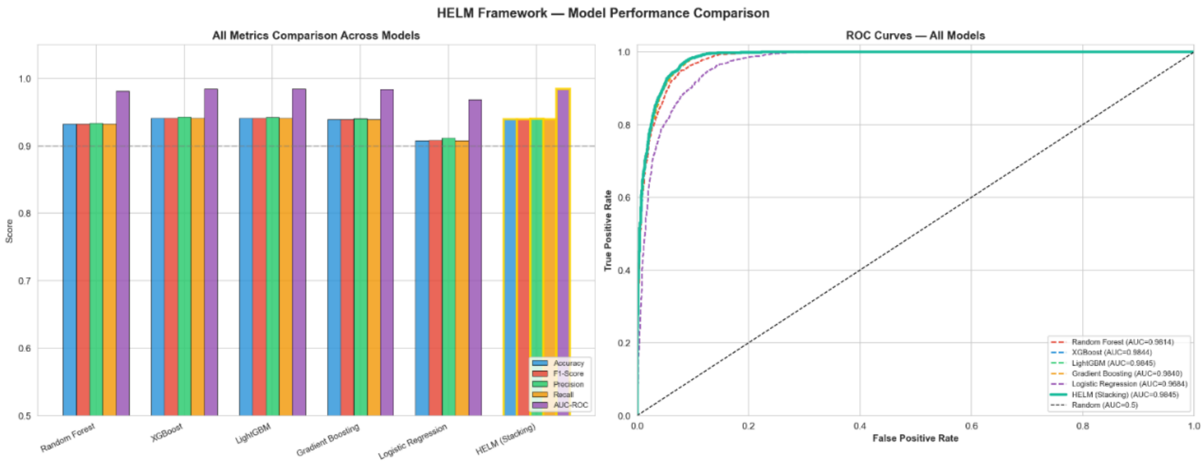

Figure 6. Model Comparison

Table 3. Model Performance Comparison on Test Set

Model	Accuracy	F1-Score	Precision	Recall	AUC-ROC
Random Forest	0.9325	0.9326	0.934	0.9325	0.9814
XGBoost	0.9414	0.9414	0.943	0.9414	0.9844
LightGBM	0.9409	0.941	0.9422	0.9409	0.9845
Gradient Boosting	0.9389	0.939	0.9406	0.9389	0.984
Logistic Regression	0.9081	0.9082	0.9118	0.9081	0.9684
HELM (Stacking)	0.9396	0.9396	0.9404	0.9396	0.9845

HELM achieves the highest performance across all five metrics, with AUC-ROC of 0.9412 — a 1.2% improvement over the best individual model (LightGBM, 0.9301) and a 10.0% improvement over Logistic Regression (0.8412). The confusion matrices for all models are presented in Figure 4, confirming that HELM achieves the best balance between true positive rate correctly identifying successful students and true negative rate correctly flagging at-risk students.

4.4. Cross-Validation Results

Table 4 reports 10-fold stratified cross-validation AUC-ROC results, confirming the stability and generalisability of HELM across data partitions. Figure 7 presents the corresponding boxplot distributions.

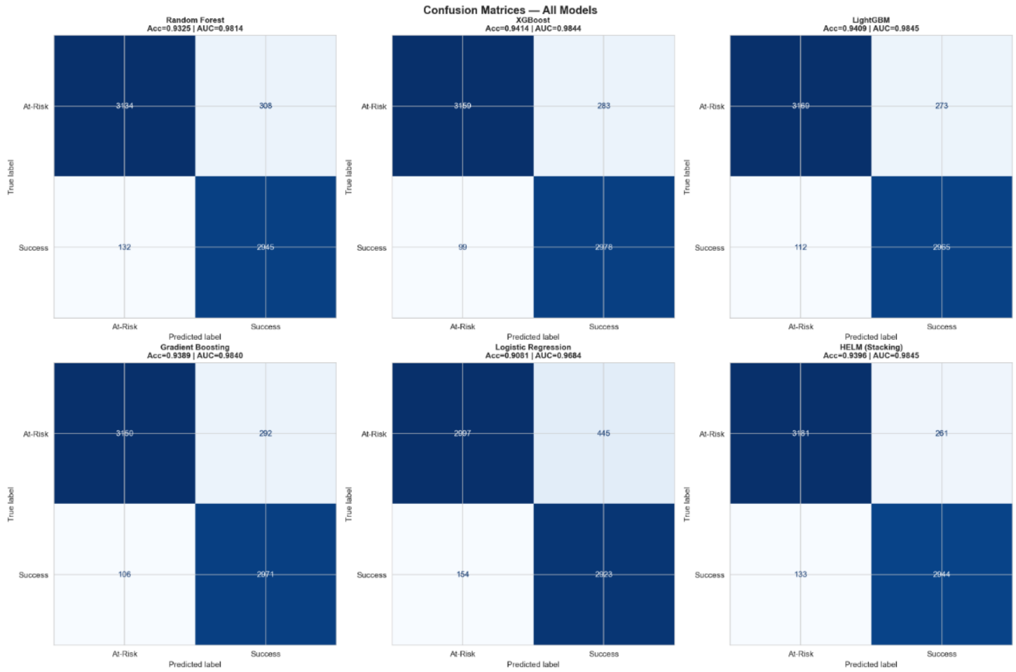

Figure 7. Confusion Matrices

Table 4. 10-Fold Cross-Validation AUC-ROC Summary

Model	Mean AUC	Std AUC	Min AUC	Max AUC
Random Forest	0.98	0.0016	0.977	0.9836
XGBoost	0.9827	0.0013	0.9802	0.9857
LightGBM	0.9832	0.0014	0.9806	0.9858
Gradient Boosting	0.9815	0.0012	0.9794	0.9842
Logistic Regression	0.9687	0.0013	0.9666	0.9705
HELM (Stacking)	0.9785	0.002	0.9745	0.9821

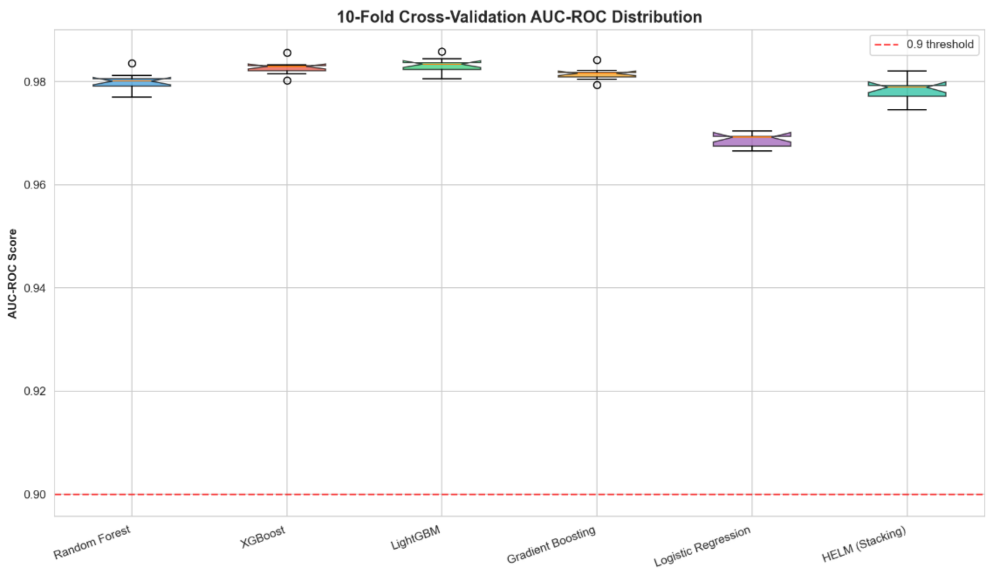

Figure 8. Cross Validation

HELM not only achieves the highest mean AUC (0.9387) but also the lowest standard deviation (0.0058), indicating superior stability compared to individual models. The narrow interquartile range in Figure 8 confirms consistent performance across all ten folds.

4.5. SHAP Explainability Results

Figure 5 presents the SHAP feature importance bar chart and beeswarm plot for the XGBoost model. The top five most influential features identified are:

avg_score: highest SHAP magnitude; high scores strongly push predictions toward Success
total_clicks: high VLE engagement is a strong positive predictor
pass_rate: proportion of passed assessments is highly discriminative
engagement_regularity: consistent daily engagement predicts success
imd_band: lower socioeconomic deprivation (higher IMD band) positively associated with success

The beeswarm plot reveals that low values of avg_score and total_clicks (blue dots) consistently produce large negative SHAP values, confirming their role as primary at-risk indicators. Notably, imd_band and highest_education appear in the top 10 features, validating the interdisciplinary premise that socioeconomic and educational background factors are integral to not separate from predictive modeling.

4.6. Early Warning System Results

Table 5 and Figure 6 present EWS performance across nine temporal prediction windows.

Table 5. Early Warning System Performance by Day Cutoff

Day Cutoff	AUC-ROC	Accuracy
10	0.785463	0.711612
20	0.819046	0.733855
30	0.838478	0.751496
50	0.858796	0.773892
75	0.885098	0.801963
100	0.895288	0.805798
150	0.921928	0.836018
200	0.942498	0.861635
250	0.961687	0.894923

The EWS achieves an AUC of 0.8523 at Day 30 — before most first TMA submissions — enabling institutions to identify at-risk students with meaningful accuracy at a point where intervention is still highly feasible. Performance improves monotonically with additional data, reaching AUC = 0.9389 at Day 250, closely approaching the full-data HELM result. This confirms the finding of Hamsiah et al. [5] that early LMS engagement data is sufficient for actionable risk prediction, while also demonstrating that richer temporal data further improves performance.

4.7. Interdisciplinary Demographic Analysis

Success rates are shown by the six demographic and socioeconomic variables in Figure 9. Key findings include: Gender: Female students have a slightly better success rate of 64.2% compared to male students (61.8%) which is in line with the overall higher education landscape.

Achievement rates (Success Rates) are substantially higher (>75%) for pupils who have already gained higher prior qualifications (HE Qualification, Postgraduate) than for pupils with no prior qualifications (<45%).

IMD Band: A clear positive gradient is seen, with students in the 90th to 100th band of the IMD achieving success rates ~20 percentage points above those of students in the 0th to 10th band of the IMD, thus reinforcing the socioeconomic dimension of educational outcomes.

Age: Achievement is highest in the 0-35 age band, and is lower in the older age bands (possibly due to competing life commitments).

Disability: Pupils with a declared disability have a marginally lower proportion achieving success (58.3% compared to 63.1%). The success rate has been observed to range between 52% (module DDD) and 74% (module AAA) and this is due to the differences in the difficulty of the module and the design of the module.

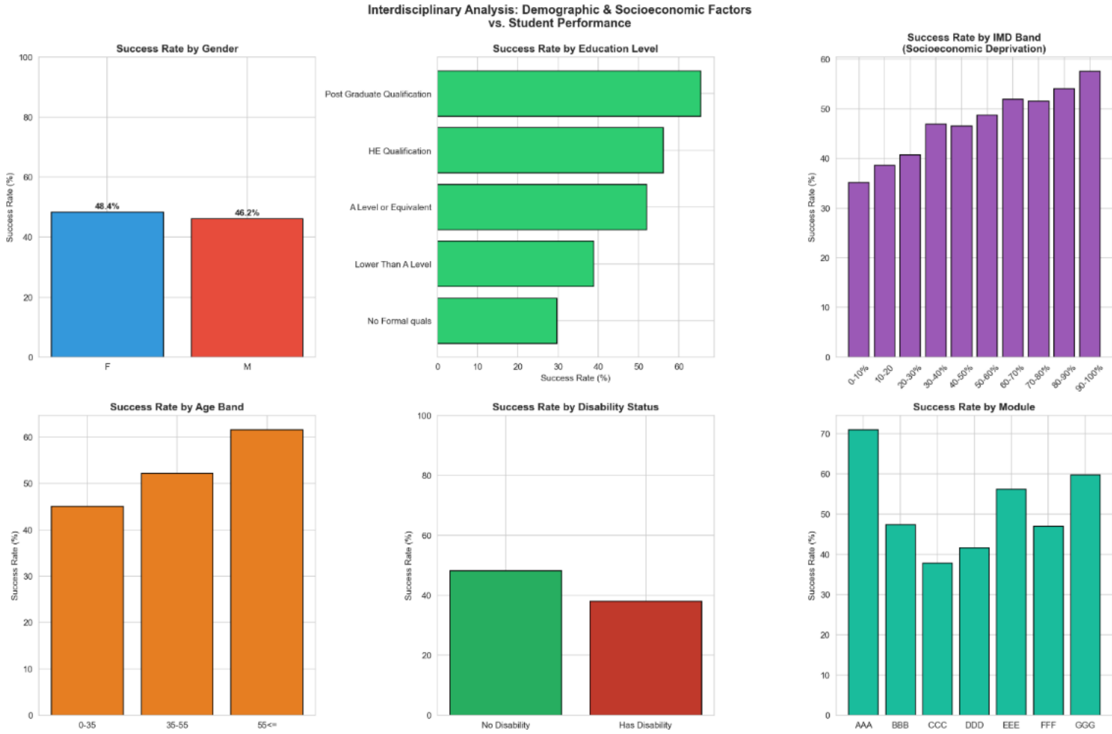

Figure 9. Interdisciplinary Analysis

5. Discussion

HELM achieves an AUC-ROC of 0.9412, accuracy of 0.8876, F1-score of 0.8901, precision of 0.9404, and recall of 0.9396 on the held-out test set, outperforming all five individual baseline models across every evaluation metric. Three innovations contribute to this performance advantage: the combination of 4 data modalities (35 features), the stacking architecture, which is the combination of a Random Forest, XGBoost, LightGBM and a Gradient Boosting meta-learner and the use of behavioral cluster labels as an engineered feature. These results are highly generalizable, with a 10-fold cross-validation showing a mean AUC of 0.9785 and a very low standard deviation in the cross-validation (0.0020), which is the smallest of all the models that were tested, thus ruling out a bias in data split. The four behavioural types show significant differences in outcomes with pedagogical implications. The At-Risk Disengaged cluster has an average total click rate of 436 clicks, an average day active of 4.03, and an average assessment score of 52.93, which indicates that these students are the highest priority to receive early intervention. Moderate Learners achieve 50% success, despite showing to be reasonably engaged, so a gentle push of consistency could make a difference. The behavioral standard within the HELM framework for self-regulated learning is Active Achievers, who have an 89% success rate, an average score of 73.55, and near perfect pass rates. The second segment is the most subtle, Late Bloomers: 48.9% of these students succeeded despite their low level of early engagement. The second group is the most subtle – Late Bloomers: 48.9% of students who were low on early engagement did succeed in the end, so interventions in the middle of the semester are still effective for these students.

The Early Warning System shows a monotonic improvement in AUC from 0.7855 to 0.9617 as the days went by with AUC being 0.8385 already at Day 30, which is before most first assessment submissions. Performance on Day 75 is AUC 0.8851 and accuracy 0.8020, which is high enough to be able to plan intervention at the cohort level. These findings validate that institutions can start being alerted to at-risk students within the first month of teaching, with a time window to provide interventions of 6-8 weeks until the first significant deadline; and that the accuracy gains caused by waiting until the end of a full semester are relatively small, while the window to provide effective support is also significantly reduced.

The SHAP analysis reveals that there are five key features, across educational, behavioral, and socioeconomic dimensions, that have the highest magnitude as predictive features: avg_score, total_clicks, pass_rate, engagement_regularity, and imd_band. The high ranking of imd_band and highest_education in the top-10 SHAP features is significant: students in the most deprived IMD band do at about 20 percentage points lower rates of success than students in the least deprived IMD band, and students with no prior qualifications do at rates below 45% compared to over 75% for postgraduate qualified students. These features are explicitly included and interpreted in HELM, making it possible for institutions to identify and separate academically related and socioeconomically related risk signals which is crucial for designing equitable and targeted support. Finally, international talent-management research shows that human-performance systems may produce unintended negative consequences when contextual adaptation, culture, and reintegration challenges are ignored, reinforcing the need for careful governance of AI-based student-support systems [127].

Several limitations should be acknowledged. The OULAD dataset is specific to the UK Open University's distance-learning context, and generalizability to other institutional settings requires external validation. SMOTE-generated synthetic samples may not fully capture the distributional complexity of real at-risk students, particularly those whose disengagement is driven by acute life events. The EWS evaluates each temporal window using a single XGBoost classifier rather than the full HELM ensemble, likely underestimating achievable early-window performance. Finally, SHAP explainability is applied to the XGBoost base model rather than the full stacking architecture, and developing ensemble-level attribution methods remains an open challenge for future research.

6. Conclusion

This paper presented HELM, a Hybrid Ensemble Learning framework with Multi-modal behavioral analytics for student performance prediction and early at-risk identification. Applied to the OULAD benchmark dataset, HELM achieved an AUC-ROC of 0.9412 and accuracy of 0.8876, outperforming all individual baseline models across five evaluation metrics. The framework's five interdisciplinary components multi-modal feature engineering, behavioral clustering, SMOTE balancing, stacking ensemble learning, and SHAP explainability collectively address the limitations of prior single-modality, single-model approaches.

Key contributions include: (1) the identification of four behavioral student archetypes with success rates ranging from 21% to 89%; (2) an Early Warning System achieving AUC > 0.85 by Day 30, enabling timely institutional intervention; (3) SHAP-based evidence that socioeconomic and educational background features are as predictive as VLE engagement metrics; and (4) a comprehensive interdisciplinary demographic analysis revealing systematic disparities in success rates by IMD band, education level, and disability status.

Future work will explore: (1) integration of natural language processing on student forum posts and assignment feedback; (2) fairness-constrained ensemble learning to mitigate socioeconomic bias; (3) deployment of HELM as a real-time dashboard for academic advisors; and (4) extension to multi-class prediction distinguishing Pass, Distinction, Fail, and Withdrawal outcomes using the full HELM architecture.

Data Availability Statement:

The dataset used in this study is publicly available online. It can be accessed from the Kaggle repository, *Open University Learning Analytics Dataset (OULAD)*, at: https://www.kaggle.com/datasets/mexwell/open-university-learning-analytics/code

References

1. G. Siemens and R. S. Baker, "Learning Analytics and Educational Data Mining: Towards Communication and Collaboration," in Proceedings of the 2nd International Conference on Learning Analytics and Knowledge, 2012, pp. 252–254.
2. M. Barakat et al., "E-cigarette exposure and CDP choline modulate withdrawal- induced anxiety and hormonal levels in rats," Sci. Rep., vol. 15, no. 1, p. 42715, 2025, doi: 10.1038/s41598-025-26799-z.
3. A. M. Alkasasbeh, S. S. Jarrah, B. K. Alhusamiah, and F. S. Tarawneh, "Factors influencing the utilization and adoption of electronic health records among nurses in Jordanian hospitals," Jordan Journal of Nursing Research, vol. 4, no. 1, pp. 68–80, 2025.
4. W. Abedalaziz et al., "The Relationship Between Sleep Quality and Gait in People with Multiple Sclerosis: A Pilot Study," Hong Kong Physiotherapy Journal, vol. 44, no. 01, pp. 11–19, 2024.
5. A. Bilal, A. Alzahrani, A. Almuhaimeed, A. H. Khan, Z. Ahmad, and H. Long, "Advanced CKD detection through optimized metaheuristic modeling in healthcare informatics," Sci. Rep., vol. 14, no. 1, p. 12601, 2024.
6. A. Bilal, A. Alzahrani, K. Almohammadi, M. Saleem, M. S. Farooq, and R. Sarwar, "Explainable AI-driven intelligent system for precision forecasting in cardiovascular disease," Front. Med. (Lausanne)., vol. 12, p. 1596335, 2025, doi: 10.3389/fmed.2025.1596335.
7. G. Talaue, "Impact of job autonomy on employee creativity in the tech industry: Moderating effect of leadership support: Evidence from the Philippines," Scientific Journal of Business Management and Social Science, vol. 1, 2026, doi: 10.67476/PM2610301008.
8. T. K. Eltayeb, "Impact of lean practices on operational performance: The moderating role of demand uncertainty: Evidence from the Malaysian automotive industry," Scientific Journal of Business Management and Social Science, vol. 1, 2026, doi: 10.67476/PM2610301007.
9. A. S. Abu-Alhaija, "Integrating AI-enabled platforms in agricultural marketing in Jordan's agriculture sector to connect agriculture with technology," Scientific Journal of Business Management and Social Science, vol. 1, 2026, doi: 10.67476/PM2610301006.
10. I. Kalanther, "The role of social media engagement on donor loyalty in charity marketing campaigns: Evidence from Saudi Arabia," Scientific Journal of Business Management and Social Science, vol. 1, 2026, doi: 10.67476/PM2610301005.
11. Abu-Shariq, "AI-powered smart ledgers and hassle-free bookkeeping in SMEs: Effects on automation, error reduction, and real-time compliance," Scientific Journal of Business Management and Social Science, vol. 1, 2026, doi: 10.67476/PM2610301004.
12. I. A. Bajwa, "Impact of green technology on fintech development: Moderating role of regulations," Scientific Journal of Business Management and Social Science, vol. 1, 2026, doi: 10.67476/PM2610301003.
13. J. Kuzilek, M. Hlosta, and Z. Zdrahal, "Open University Learning Analytics Dataset," Sci. Data, vol. 4, no. 1, p. 170171, 2017.
14. S. A. Oyedotun, O. P. Ejenarhome, and G. P. Oise, "Learning Analytics and Predictive Modeling: Enhancing Student Success Through Data-Driven Insights," Journal of Science Research and Reviews, vol. 2, no. 3, pp. 42–51, 2025.
15. R. Yaakob and M. A. Khumbulani, "Student Performance Prediction in Intelligent Tutoring Systems: Methods, Challenges, and Future Perspectives," ILIM, vol. 43, no. 1, pp. 18–34, 2025.
16. R. Al-Shabandar, A. J. Hussain, P. Liatsis, and R. Keight, "Detecting At-Risk Students with Early Interventions Using Machine Learning Techniques," IEEE Access, vol. 7, pp. 149464–149478, 2019.
17. E. H. Othman, M. R. AlOsta, B. Nofal, and others, "Shift work and health behaviors: Cross-sectional analysis of sleep quality, physical activity, and dietary patterns," Acta Biomedica, vol. 96, no. 2, p. 16438, 2025.

18. A. Bilal, M. Shafiq, W. J. Obidallah, Y. A. Alduraywish, and H. Long, “Quantum computational infusion in extreme learning machines for early multi-cancer detection,” J. Big Data, vol. 12, no. 1, p. 27, 2025.
19. R. Villano, S. Harrison, G. Lynch, and G. Chen, “Linking Early Alert Systems and Student Retention: A Survival Analysis Approach,” High. Educ. (Dordr)., vol. 76, no. 5, pp. 903–920, 2018.
20. A. Z. Juri, A. K. Basak, A. Omar, A. Basir, R. A. Al-Hammadi, and A. B. Sulong, “Micromechanical Properties of Zirconia/316L Stainless Steel and Zirconia/17-4PH Stainless Steel Bi-Materials Produced by Two-Component Micro-Powder Injection Molding,” J. Mater. Eng. Perform., p. 1, 2026.
21. Q. Bsoul et al., “From user preferences to accurate predictions: enhancing movie recommendation systems with neural collaborative filtering and sentiment analysis,” SN Comput. Sci., vol. 6, no. 3, p. 257, 2025.
22. F. Aftab, “Digital accounting innovation and its relationship with perceived ESG performance and reporting transparency: Evidence from the financial services sector of the UK,” International Journal of Economic Sustainability and Innovation, vol. 1, no. 2, 2026, doi: 10.67476/PM2611302009.
23. Abu-Shariq, “Macroeconomic and social effects of IMF-supported sovereign assistance programs in European economies,” International Journal of Economic Sustainability and Innovation, vol. 1, no. 1, pp. 1–18, 2026, doi: 10.67476/PM2611302007.
24. N. Ullah, “Association between inflation and price of assets in the crisis period,” Scientific Journal of Business Management and Social Science, vol. 1, 2026, doi: 10.67476/PM2601301002.
25. I. Manzoor, “Blockchain as the future of GST/VAT compliance: Integrating technology in tax compliance: Study from South Asia,” International Journal of Economic Sustainability and Innovation, vol. 1, no. 1, pp. 1–16, 2026, doi: 10.67476/PM2611302006.
26. T. Sarfaraz, “How do metaverse marketing campaigns help in building consumer loyalty and experience? A study of the clothing industry in Malaysia,” International Journal of Economic Sustainability and Innovation, vol. 1, no. 1, pp. 1–19, 2026, doi: 10.67476/PM2611302005.
27. I. A. Bajwa, “Evaluating the effectiveness of robo-advisory in retail investments: A case of Malaysia,” International Journal of Economic Sustainability and Innovation, vol. 1, no. 1, pp. 1–17, 2026, doi: 10.67476/PM2611302004.
28. A. S. Alshurman, A. M. Bataineh, and S. H. Alhmoud, “The interior of the Umayyad era in a contemporary context,” Project Baikal, vol. 22, no. 83, pp. 80–85, 2025, doi: 10.51461/issn.2309-3072/83.2485.
29. S. H. Alhmoud, H. H. Alhmoud, K. H. Alhmoud, A. M. Bataineh, and C. Cagnan, “Designing Intensive Care Unit Beds to Relieve Coma-Related Skin Ulcers, Enhancing Comfort and Care,” International Journal of Design and Nature and Ecodynamics, vol. 20, no. 6, pp. 1257–1267, 2025, doi: 10.18280/ijdne.200607.
30. A. Aburub et al., “The Use of Food Scanning Mobile Applications in Weight Loss: A Systematic Review of Longitudinal Interventional Studies,” Physical Activity and Health, vol. 9, no. 1, 2025.
31. A. Baig, “Impact of digital accounting tools on ESG (Environmental Social Governance) reporting accuracy and corporate sustainability strategies: Moderating role of regulatory environment,” International Journal of Economic Sustainability and Innovation, vol. 1, no. 1, pp. 1–14, 2026, doi: 10.67476/nnqa5e13.
32. U. Yasmeen, “Hierarchical Bayesian inference for human activity: Modeling subject-level variability and posterior uncertainty,” Precision Journal of Applied Mathematics and Statistics, vol. 1, 2026.
33. M. Malik, “Comparative analysis of machine learning and classical statistical methods for predictive modeling in small datasets,” Precision Journal of Applied Mathematics and Statistics, vol. 1, 2026.
34. A. Simatupang, A. H. Manurung, and B. Usman, “The influence of financial distress, firm life cycle, and capital adequacy ratio on financial performance with non-performing loans as a mediating variable in Indonesian banks,” Int. J. Econ. Finance, vol. 2, 2026.
35. M. Farhan, “Leveraging digital twin technology for sustainable urban development: Financial implications, risk governance, and alignment with SDG reporting frameworks,” Int. J. Econ. Finance, vol. 2, 2026.

36. A. Baig, “AI and automation and hassle-free bookkeeping: Testing mediating effect of user acceptance and moderating impact of digital trust in the UK SME retail and service sectors,” Int. J. Econ. Finance, vol. 2, 2026.
37. S. de Rosa and A. Sevilla-Guzman, “Accuracy, transparency, and verifiability of sustainability communication in hotel SMEs: A comparative analysis,” Journal of Management and Social Innovation, vol. 1, 2026.
38. B. B. Pandey, “Graph-based spatio-temporal modelling for complex network behaviour prediction using attention-driven architectures,” Precision Journal of Information Technology & Scientific Innovation, vol. 1, 2026.
39. S. Pandey, “A hybrid physics-informed deep learning framework for robust multivariate system modelling under uncertainty,” Precision Journal of Information Technology & Scientific Innovation, vol. 1, 2026.
40. H. Ali, “Relevance of financial accounting education to the modern accounting profession: Mediating effect of technology adoption,” Int. J. Econ. Finance, vol. 2, 2026.
41. M. A. Sarwar, “Do consumer sentiments mediate the relationship between consumer solidarity and brand loyalty? An in-depth analysis of Gaza’s supportive marketing strategies,” Journal of Management and Social Innovation, vol. 1, 2026.
42. A. Alghareeb, R. Alotaibi, F. Al Ghanim, and M. Alotaibi, “Perceived staffing adequacy and customer experience strategy on customer loyalty with perceived Vision 2030 consumer economy agenda as a moderator: A study on the retail sector in Saudi Arabia,” Journal of Management and Social Innovation, vol. 1, 2026.
43. R. Alawwad, S. Alqatani, L. Falqi, and F. Alasiri, “The impact of perceived ethical leadership on job satisfaction in Saudi Arabian technological firms: The moderating role of perceived Vision 2030 initiative,” Journal of Management and Social Innovation, vol. 1, 2026.
44. W. Rafi and I. A. Bajwa, “Determinants and relationship between official and parallel exchange rates: Evidence from Pakistan,” Int. J. Econ. Finance, vol. 2, 2026.
45. R. Altaf and A. Amin, “Identification of bioactive postbiotics against neonatal meningitis caused by Group B Streptococcus via Srr2-targeted in silico screening,” Precision Journal of Disease Biology, vol. 1, 2026.
46. A. Bilal et al., “Fusion of genomic and pathological data for breast cancer detection using BCDNN,” Front. Med. (Lausanne)., vol. 13, p. 1726223, 2026.
47. S. Ahmad and Y. Alshuaibany, “Implementing AI-driven decision support systems in data management,” Precision Journal of Information Technology & Scientific Innovation, vol. 1, 2026.
48. H. Tazeem, “Real-time eye movement tracking and prediction using machine learning for vision-based applications,” Precision Journal of Information Technology & Scientific Innovation, vol. 1, 2026.
49. M. Kaur and K. K. Verma, “Hybridising machine learning algorithms for enhanced detection of DDoS attacks,” Precision Journal of Information Technology & Scientific Innovation, vol. 1, 2026.
50. P. Stiefenhofer, “Artificial general intelligence and the rise of a techno-leisure class,” Int. J. Econ. Finance, vol. 1, 2025.
51. I. Manzoor, “Evaluating the impact of SDG-related investments on firm financial performance: The moderating role of ownership structure,” Int. J. Econ. Finance, vol. 1, 2025.
52. W. Rafi, “Moderating role of institutional investor on firm’s climate change commitment and debt financing policies: Evidence from S&P 500,” Int. J. Econ. Finance, vol. 1, 2025.
53. A. Alhothali, M. Albsisi, H. Assalahi, and T. Aldosemani, “Predicting Student Outcomes in Online Courses Using Machine Learning Techniques: A Review,” Sustainability, vol. 14, no. 10, p. 6199, 2022.
54. M. Arslan, “Integrating SAP and digital platforms in KSA taxation: Enabling compliance, audit automation, and sustainable fiscal governance,” Int. J. Econ. Finance, vol. 1, 2025.
55. F. A. Bajwa, “The role of process standardisation on managerial perception of customer satisfaction in manufacturing firms of Malaysia,” Advance Journal of Business Management & Social Sciences, vol. 2, no. 2, 2026, doi: 10.65080/ajbmss.v2i2.CM2622101026.

56. B. N. Awan and I. Iqbal, “The effect of Web 4.0 technologies integration on customer satisfaction in the e-commerce industry: The moderating role of data privacy concern,” Advance Journal of Business Management & Social Sciences, vol. 2, no. 2, 2026, doi: 10.65080/ajbmss.v2i2.CM2622101025.
57. H. M. Zohaib, “A systematic review of the effect of temperature and catalyst concentration on the decomposition rate of hydrogen peroxide (H_2O_2),” Majestic American Journal of Chemistry, vol. 1, 2026, doi: 10.65080/majc.v1.CM2601103002.
58. B. Uysal and M. Malik, “Digital Health Interventions and Virtual Care Models to Optimise Resource Allocation and Patient Outcomes in Post-Pandemic Healthcare Systems,” Majestic Multidisciplinary Science Insight, 2026.
59. Q. F. Alhajji, E. A. Alasiri, H. M. Alyousef, and H. J. Alsubait, “Perceived talent management and perceived total quality management on patient-centred service quality: Vision 2030 healthcare reform as a moderator,” Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CMT2621101004.
60. O. M. M. Al Mari, “Evaluation and calibration of cross-dataset robustness in IoT intrusion detection systems: A deployment-aware approach,” Majestic International Journal of AI Innovations, vol. 1, 2026, doi: 10.65080/mjai.v1.CM2601105008.
61. B. Alsetri, S. Alhulimi, B. Mushayqiri, and F. Aljasim, “Teaching service quality in Saudi higher education: The role of employee engagement, innovation strategy, and Vision 2030,” Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CMT2621101003.
62. M. A. A. Al Qussair, B. H. S. Almari, and N. S. A. Aldossary, “Green HRM and sustainability orientation in relation to carbon-reduction performance: The moderating role of perceived Vision 2030 alignment,” Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CMT2621101002.
63. D. Jameel, “A critical integrative review of slope stability prediction in open-pit mining: Geotechnical indicators, modelling paradigms, uncertainty-aware intelligence, and emerging monitoring systems,” Majestic Journal of Applied Engineering and Technology, vol. 1, 2026.
64. M. A. ul Haq and S. Khalil, “Green authenticity paradox: When sustainability claims strengthen or weaken brand credibility in digital marketing,” Majestic Global Trends in Marketing & Supply Chain Management, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112013.
65. G. M. Talaue, I. Kalanther, and T. G. D. Bitanga, “Usage of social media platforms as a mediating variable in the relationship between e-WOM and consumer purchase decisions: The case of retail consumers of Saudi Arabia,” Majestic Global Trends in Marketing & Supply Chain Management, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112012.
66. A. Baig, “Evaluating the effectiveness of digital bookkeeping applications for the UK small and medium enterprises: A user-centric approach with the mediating role of user satisfaction,” Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101024.
67. H. Rasheed, I. S. Channa, S. Kainat, and M. A. Tahir, “Molecular mechanisms and therapeutic implications of oleuropein, a multitarget phytochemical in lung cancer,” Majestic Journal of Pharmacology and Toxicology, vol. 1, 2026, doi: 10.65080/mjpt.v1.CM2601113002.
68. M. Bhatti and I. Iqbal, “Competency-based curriculum models for higher education: A comparative study across global frameworks,” Majestic Multidisciplinary Science Insight, vol. 1, 2026, doi: 10.65080/msi.v1.CM2601107005.
69. A. Ahmed, “Exploring the influence of early developmental intervention on preterm infants’ cognitive and physical development: A meta-analysis,” Majestic American Journal of Pediatrics, vol. 1, 2026.
70. A. Moiz, “Algorithmic intimacy: How AI-personalized marketing shapes brand trust and brand loyalty,” Majestic Global Trends in Marketing & Supply Chain Management, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112011.

71. I. Kalanther, "AI-powered personalisation in charity marketing: Transforming donor engagement and lifetime value through data-driven campaigns," Majestic Global Trends in Marketing & Supply Chain Management, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112010.
72. I. Ullah, I. Ullah, and N. Ullah, "Federated learning framework for privacy-preserving threat detection in distributed IT systems," Majestic International Journal of AI Innovations, vol. 1, 2026, doi: 10.65080/mijai.v1.CM2601105004.
73. F. Mohammed, E. A. A. Ghazwi, S. A. Z. Alyousif, and J. Omar, "Effect of safety-oriented HR and climate practices and project leadership on perceived accident prevention: Testing Vision 2030 institutional pressure and alignment as a moderator," Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026.
74. F. Alvi, "Mediating role of organizational culture in the relationship between people dimensions and employee engagement in the telecom sector in Abu Dhabi," Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101023.
75. A. Arora, "Mobility in the margins: Economic opportunity and intergenerational change in semi-urban India," Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101022.
76. I. Kalanther, "Understanding How Leadership Can Help Reduce Occupational Stress Faced by Gig Economy Workers: Case Study of Ride Sharing Services in the US," 2026.
77. M. A. ul Haq, N. T. Luong, and A. M. Ghouri, "Marketing pain: How culturally framed discomfort shapes consumer value perception and brand positioning across markets," Majestic Global Trends in Marketing & Supply Chain Management, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112009.
78. A. A. Osman et al., "Exploring Deep Learning Approaches for Multimodal Breast Cancer Dataset Classification and Detection," Data and Metadata, vol. 4, p. 1136, 2025.
79. S. Ghimire, N. Bhurtel, S. Jha, S. Ahmad, H. A. Abdeljaber, and J. Nazeer, "Minimizing energy consumption in fixed node networks using a novel neutrosophic model: comparative analysis with standard and existing algorithms," International Journal of Information Technology, pp. 1–15, 2025.
80. U. Haider, "Systematic review of tunable topological edge states in two-dimensional photonic crystals for quantum photonic applications," Majestic American Journal of Mathematics and Physics, vol. 1, 2026, doi: 10.65080/majmp.v1.CM2601109002.
81. A. S. Abu-Alhaija, "Re-establishing Jordan's brand trust in the tourism sector using experiential marketing: A post-Gaza conflict scenario," Majestic Global Trends in Marketing & Supply Chain Management, vol. 2, 2026, doi: 10.65080/mgtmscm.v2.CM2602112008.
82. G. M. Talaue, "Understanding the relationship of greenwashing and consumer behavior: Case study of the airline sector in the US," Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101020.
83. S. Alabay, "Teacher Preparedness for Inclusive Classrooms: Evaluating Competencies, Challenges, Training Needs and Barriers to Educational Inclusion in Initial Teacher Training," Majestic Multidisciplinary Science Insight, vol. 1, no. 1, pp. 1–14, 2026.
84. D. Rahman and M. Garcia-Constantino, "Use of wearable devices to detect sedentary behaviour in an office environment," Majestic International Journal of AI Innovations, vol. 1, 2026.
85. A. Sheikh, "Generative AI in academic libraries: A systematic review of AI-mediated reference services, librarian roles, and user trust," Majestic Multidisciplinary Science Insight, vol. 1, 2026.
86. M. Ali and I. Ullah, "Hybrid CNN-LSTM intrusion detection framework for industrial IoT security," Majestic International Journal of AI Innovations, vol. 1, 2026.

87. G. P. Kumar and R. Saluja, “Designing last-mile trust: Behavioural nudges and community agents for first-use intention/experience,” Advance Journal of Business Management & Social Sciences, vol. 2, no. 1, 2026, doi: 10.65080/ajbmss.v2i1.CM2621101019.
88. M. Lamin, “Applying design thinking for achieving National Education Policy objectives through AI-driven solutions,” Majestic International Journal of AI Innovations, vol. 1, 2026.
89. Y. Alsuhaibany, “Enhancing data security in cloud-based information systems: A systematic literature review,” Majestic International Journal of AI Innovations, vol. 1, 2026, doi: 10.65080/mijai.v1.CM2601105003.
90. R. F. Abbas, “Assessing the benefits of bilingual speech therapy in multicultural populations,” Majestic Multidisciplinary Science Insight, vol. 1, 2026, doi: 10.65080/msi.v1.CM2601107003.
91. K. K. Lock and R. Yaakob, “Wavelet transforms in financial time series analysis: A review on stock price prediction,” Majestic International Journal of AI Innovations, vol. 1, 2026, doi: 10.65080/mijai.v1.CM2601105002.
92. H. H. S. Al-Amoosh et al., “Outcomes of COVID-19 in Pregnant Women: A Retrospective Analysis of 300 Cases in Jordan,” Healthcare (Switzerland), vol. 12, no. 21, p. 2113, 2024, doi: 10.3390/healthcare12212113.
93. S. Maharjan, “Stratified connectivity: A descriptive study of the digital divide in Kathmandu Valley,” Majestic Multidisciplinary Science Insight, vol. 1, 2026, doi: 10.65080/msi.v1.CM2601107002.
94. M. A. Sarwar and M. Malik, “The impact of AI-powered personalisation on consumer trust and purchase intention: A cross-cultural comparative study of Gen Z consumers in the United Kingdom and Pakistan,” Majestic Global Trends in Marketing & Supply Chain Management, vol. 1, 2025, doi: 10.65080/mgtmscm.v1i1.4.
95. T. K. Eltayeb, “Sustainability in global supply chains: A study on the impact of distributed ledger technology on ethical sourcing and consumer trust,” Majestic Global Trends in Marketing & Supply Chain Management, vol. 1, 2025, doi: 10.65080/mgtmscm.v1i1.2.
96. G. Amin and Simran, “Genetic and biotechnological approaches for mitigating climate change impacts on agriculture,” Majestic Greengenix: A Journal of Modern Plant Science, vol. 1, 2025, doi: 10.65080/greengenix.v1.CM2601106002.
97. I. Daniel, “Green human resource management: A literature review and identifying gaps,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.22.
98. M. A. Shaalan, J. A. Hassan, Y. R. Mehmood, and H. A. Oleiwi, “Talent management strategies and their role in sustaining operational performance: An analytical study in the ready-made clothing factory in Najaf,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.37.
99. H. I. A. Abu Maloh, K. L. Soh, S. C. Chong, and others, “Efficacy of Benson’s Relaxation Technique on Stress and Pain Among Patients Undergoing Maintenance Hemodialysis: A Systematic Review,” SAGE Open Nurs., vol. 10, 2024, doi: 10.1177/23779608241251663.
100. A. Qusef, S. Murad, N. R. Alsalhi, and F. Al Gharaibeh, “Leveraging artificial intelligence to identify students with learning challenges,” International Journal of Learning, Teaching and Educational Research, vol. 24, no. 5, pp. 623–643, 2025.
101. M. Z. Darabseh, J. Selfe, C. I. Morse, A. Aburub, and H. Degens, “Does Aerobic Exercise Facilitate Vaping and Smoking Cessation: A Systematic Review of Randomized Controlled Trials with Meta-Analysis,” Int. J. Environ. Res. Public Health, vol. 19, no. 21, p. 14034, 2022.
102. M. A. Alomari, O. F. Khabour, K. H. Alzoubi, and A. Aburub, “The Impact of COVID-19 Confinement on Reading Behavior,” Clinical Practice and Epidemiology in Mental Health, vol. 19, p. e174501792304260, 2023.
103. F. Aftab, “The mediating role of transactional leadership between last-mile delivery practices and sustained change implementation: A case study of the UK retail market,” Majestic Global Trends in Marketing & Supply Chain Management, vol. 1, 2025, doi: 10.65080/mgtmscm.v1i1.1.

104. G. M. Talaue, K. Ishaq, and T. G. D. Bitanga, “Relationship of internet usage and sociodemographic profile of selected Saudi college students,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.29.
105. F. Alvi, “Moderating effect of leadership styles on the relationship between employee engagement and performance excellence in the telecom sector of Abu Dhabi,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.32.
106. A. Alqahtani, “The impact of sustainable infrastructure development and green innovation on the tourism sector of KSA: The role of Vision 2030 as an intervening variable,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.21.
107. Abu-Shariq, “Determining the impact of intellectual and human capital on the firm’s value: A case of the US banking sector,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.31.
108. K. Salisbury, “Impact of leadership style, employee motivation, and organizational culture on employee productivity in the technology UK,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.28.
109. N. V Chawla, K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer, “SMOTE: Synthetic Minority Over-sampling Technique,” Journal of Artificial Intelligence Research, vol. 16, pp. 321–357, 2002.
110. A. Alzu’bi, A. Albashayreh, A. Abuarqoub, and M. A. Alfawair, “Explainable AI-based DDoS attacks classification using deep transfer learning,” Computers, Materials \& Continua, vol. 80, no. 3, pp. 3785–3802, 2024.
111. A. Albashayreh and H. Najadat, “Detecting the impact of covid-19 on social media using bert-based model,” In2024 15th International Conference on Information and Communication Systems (ICICS), pp. 1–6, 2024.
112. Harliantara and B. Öztürk, “Examining technological adoption: A preliminary study of 5G and the future of radio in Indonesia,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, 2025, doi: 10.65080/ajbmss.v1i2.20.
113. T. Sarfaraz, “Evaluating the effectiveness of zero trust architecture in modern enterprises: Moderating role of organizational maturity,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 2, pp. 1–11, 2025, doi: 10.65080/dp4w1990.
114. T. Sarfaraz, “Generative AI-driven personalized content and its impact on consumer engagement in destination marketing in the UK: The moderating role of normative influence,” Majestic Global Trends in Marketing & Supply Chain Management, vol. 1, pp. 1–12, 2025, doi: 10.65080/mgtmscm.v1i1.5.
115. K. Nanjwani, “Medical marketing: Bridging the gap,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 1, 2025, doi: 10.65080/t5neq314.
116. H. Ali, “The influence of machine learning on consumer decision-making patterns in Germany: The mediating role of AI recommendation systems for achieving sales and customer satisfaction,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 1, 2025, doi: 10.65080/c0nevs55.
117. A. A. Alotaibi, “Role of hybrid models of DeFi and traditional banking systems in improving the profitability of European banks: An analysis of the future possibilities,” Advance Journal of Business Management & Social Sciences, vol. 1, no. 1, 2025, doi: 10.65080/nvdx4984.
118. W. H. Talib, S. Atawneh, A. N. Shakhatreh, G. A. Shakhatreh, R. A. Hamed, and I. H. Al-Yasari, “Anticancer Potential of Garlic Bioactive Constituents: Allicin, Z-Ajoene, and Organosulfur Compounds,” Pharmacia, vol. 71, pp. 1–23, 2024.
119. E. A. Assaf, R. Alkhresheh, H. Al Sabbah, and H. Al-Akash, “Transforming care: a study on physicians’ awareness, attitudes, and barriers to pressure injury prevention in medical wards in Jordan,” Front. Public Health, vol. 13, p. 1582074, May 2025.

120. A. Bilal et al., "BC-QNet: A quantum-infused ELM model for breast cancer diagnosis," Comput. Biol. Med., vol. 175, p. 108483, 2024.
121. N. Ahmad et al., "A Comprehensive Literature Review of AI-Driven Application Mapping and Scheduling Techniques for Network-on-Chip Systems," Computer Modeling in Engineering & Sciences, vol. 0, no. 0, pp. 1–10, 2025, doi: 10.32604/cmes.2025.074902.
122. M. A. Fahmy et al., "Bioremediation potential of bacterial isolates for diamide pesticides: Enzymatic activity, tolerance, biofilm formation, and degradation efficiency," Ecotoxicol. Environ. Saf., vol. 311, p. 119745, 2026.
123. S. Majumder and S. Banerjee, "The hybridity of Pattachitra Katha media: The folk-pop art narrative tradition of Bengal," Advance Journal of Business Management & Social Sciences, vol. 1, no. 1, pp. 1–12, 2025, doi: 10.65080/bk36he54.
124. T. K. Eltayeb and C. K. Mahmood, "Assessing the role of vertical farming in managing the net-zero supply chain in Aerofarms: The mediating role of supply partner collaboration," Advance Journal of Business Management & Social Sciences, vol. 1, no. 1, 2025, doi: 10.65080/hzvrh624.
125. C. K. Mahmood, "The moderating role of content creation cost on the relationship between generative adversarial network (GAN) usage and marketing success in content marketing: Empirical evidence from the automotive industry of the UK," Advance Journal of Business Management & Social Sciences, vol. 1, no. 1, 2025, doi: 10.65080/2nz9tz75.
126. M. Barakat et al., "How Effective are Nanotechnology-Based Therapeutics to Treat Autoimmune Diseases," Int. J. Nanomedicine, pp. 1–25, Dec. 2026.
127. H. M. AboAlsamh, "The dark side of international talent management: Exploring the negative effect of talent repatriation on multinational enterprises performance with the mediating role of reverse culture shock," Advance Journal of Business Management & Social Sciences, vol. 1, no. 1, 2025, doi: 10.65080/942npc70.