A MLOps Framework for Early Detection and Adjustment of Learner Behaviors in Fashion Manufacturing Technology Education

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Abstract

MLOps, short for Machine Learning Operations, is a practice that aims to streamline and automate the process of deploying, monitoring, and managing machine learning models in production. In the context of educational technology, MLOps can help optimize the performance of learning algorithms, ensure scalability and reliability. By implementing MLOps, educators can utilize real-time data to identify patterns of behavior that may indicate a student is struggling. This proactive approach allows timely interventions to be put in place, addressing issues before they escalate and potentially lead to academic failure. Additionally, MLOps can also help educators personalize learning experiences for students, catering to their individual needs and preferences. The participants were 60 learners enrolled in the Ready-Made Garment Manufacturing Technologies course, part of the Fashion Manufacturing Technology specialization in the Faculty of Human Sciences and Design at King Abdulaziz University. The findings of research found that integration of MLOps in educational technology has the potential to support and guide students in their learning through detecting undesirable student behaviors and adjusting early.

Keywords : MLOps; Learner behaviors; Adjusting early; Fashion Manufacturing Technology

1. Introduction

Machine Learning Operations (MLOps) represents a pivotal discipline within machine learning engineering that focuses on streamlining the end-to-end lifecycle of machine learning (ML) models—from development and deployment to maintenance and continuous monitoring. MLOps integrates practices from data science, DevOps, and information technology (IT) to ensure efficient, scalable, and reliable production workflows. Through continuous integration and continuous deployment (CI/CD) pipelines, MLOps improves the pace of model iteration, guarantees model validation and governance, and reduces operational risks associated with ML deployment [1]. The core advantages of MLOps include enhanced efficiency, scalability, reproducibility, and risk mitigation. These practices accelerate model delivery while maintaining high-quality performance and compliance with institutional or industry regulations.

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Beyond industrial applications, MLOps automation has begun to demonstrate its potential in the educational sector [2]. Automation within MLOps supports data collection, model training, deployment, and performance tracking through unified pipelines. This automation minimizes manual intervention, fosters collaboration between educators, data analysts, and IT professionals, and ensures consistent monitoring and compliance across educational systems [3]. As Silverio and Luigi (n.d.) note, MLOps automation reduces time and effort in each stage of the AI/ML lifecycle while enabling continuous model improvement and governance [4].

In recent years, MLOps has been viewed as a bridge between machine learning theory and real-world application, ensuring that deployed models remain stable and adaptive over time. It brings together machine learning, data engineering, and DevOps methodologies to optimize operational performance across the ML workflow [5]. Within educational technology, this alignment is crucial to addressing behavioral and engagement challenges among students. Previous studies indicate that feedback mechanisms and adaptive interventions can influence students' behavioral patterns and motivation in the learning process [6][7].

Integrating MLOps frameworks into educational contexts, particularly in specialized disciplines such as fashion manufacturing technology, provides an opportunity to detect and adjust undesirable learner behaviors in real time [8]. By combining data analytics, automated feedback, and iterative monitoring, educators can proactively respond to learners' needs and enhance engagement levels. Understanding the relationship between feedback, motivation, and learning outcomes remains fundamental to creating responsive and effective learning environments. Thus, this study explores the role of MLOps in detecting and managing learner behaviors within fashion manufacturing technology education, contributing to the broader discourse on AI-driven educational enhancement [9]. Particularly within domains such as fashion manufacturing and design, where digital transformation and analytics enhance learning outcomes [10].

2. Related Work

This study investigates the potential of Machine Learning Operations (MLOps) frameworks to detect and predict undesirable learner behaviors within higher education environments and to enable timely corrective interventions. The research is guided by two central questions:

1. Can MLOps effectively identify undesirable learner behaviors?
2. To what extent can MLOps facilitate early behavioral adjustments through automated, data-driven interventions?

2.1 Definition and Conceptualization of MLOps

Machine Learning Operations (MLOps) has emerged as a critical discipline that unifies machine learning, DevOps, and data engineering practices to streamline the development, deployment, and continuous maintenance of ML models in production. It emphasizes automation across the entire ML lifecycle through Continuous Integration (CI), Continuous Delivery (CD), and Continuous Training (CT). By integrating DevOps methodologies, MLOps enables automated model retraining whenever performance degradation is detected, ensuring consistent model accuracy and adaptability over time [11]. These practices have been recognized as foundational to scaling ML systems efficiently across industrial and educational contexts [12][13].

Advanced MLOps frameworks also support dynamic resource allocation and auto-scaling based on computational demands, while the incorporation of Natural Language Processing (NLP) components enhances automation and interoperability. These capabilities promote reproducibility, workflow portability, and efficient management of data and model registries, thereby optimizing ML governance and decision reliability [14][15].

2.2 MLOps Tools and Automation Frameworks

A broad range of MLOps tools have been developed to automate the ML workflow and ensure reliable model lifecycle management. On Google Cloud, platforms such as Dataflow, AI Platform Notebooks, Cloud Build, TensorFlow Extended (TFX), and Kubeflow Pipelines enable seamless orchestration of ML processes. Similarly, Amazon SageMaker on AWS provides an integrated environment for training, deploying, and monitoring machine-learning models. Several emerging cloud-based services—such as Azure ML, MLflow, and AutoML frameworks—provide integrated automation pipelines [16][17].

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Despite these advancements, existing research highlights persistent challenges concerning traceability, reproducibility, and compliance in MLOps platforms. While open-source frameworks such as MLflow and Kubeflow address certain automation aspects, standardized traceability mechanisms across the entire ML lifecycle remain limited. Consequently, comparative evaluations of MLOps systems have emphasized the need for frameworks that balance scalability, automation, and governance integrity [18][19]. Recent comparative analyses highlight the evolving maturity of open-source MLOps tools, emphasizing interoperability, experiment tracking, and workflow versioning [20][21].

2.3 Platform Evaluation and Functional Criteria

As noted by den Berg (2023), MLOps platforms are indispensable to the industrialization of artificial intelligence applications. Effective platforms must incorporate modular environments for development and production, automated training and deployment pipelines, version control for data and models, and secure monitoring infrastructures [22][23]. Studies by Kumar (2023) and Duta (2024) underscore that end-to-end MLOps solutions enable faster prototyping and reproducibility through continuous integration and scalable deployment [24][25].

Key criteria identified for evaluating MLOps platforms include:

• Data Processing Pipelines: Mechanisms for transforming raw data into analytical features often linked with a feature store.

• Feature Store Management: Systems for maintaining offline and online feature repositories to support consistent model performance.

• Model Training and Development: Infrastructure that enables scalable model training, including the flexibility to integrate major frameworks such as TensorFlow and PyTorch.

• Model Deployment and Serving: Support for real-time, batch, and streaming deployments with minimal configuration complexity.

• Monitoring and Analytics: Tools for operational oversight, including performance dashboards, error tracking, and inference monitoring.

• Workflow Automation: Capabilities for orchestrating iterative tasks and automating retraining processes to sustain continuous improvement.

Collectively, these components form the operational backbone that enables scalable and accountable machine learning pipelines in modern data-driven environments.

2.4 Prior Research in Educational Contexts

The application of MLOps and machine learning techniques in education—particularly within Learning Management Systems (LMS)—has been explored to enhance predictive analytics, personalization, and adaptive learning mechanisms.

• **Personalized Learning:** Kwak, Lee, and Kwon (2020) demonstrated that integrating machine-learning algorithms within LMS platforms could forecast student performance and enable early, customized interventions. Their study revealed that predictive models effectively identified at-risk learners and improved overall academic achievement through timely guidance. Similar work in adaptive e-learning analytics confirmed the impact of predictive feedback on retention and motivation [26][27].

• **Predictive Analytics in Education:** Papamitsiou and Economides (2014) showed that predictive analytics could significantly reduce dropout rates by detecting disengagement and behavioral decline at early stages. Their findings support the feasibility of deploying MLOps frameworks for behavioral monitoring and instructional adaptation. In addition, AI-based classroom behavior systems have shown success in mitigating disengagement through automated monitoring and gamified interventions [28][29].

• **Adaptive Learning Systems:** Brusilovsky and Millán (2007) examined adaptive systems capable of real-time content adjustment based on learner interaction data. Their research confirmed that adaptive

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mechanisms lead to measurable improvements in student outcomes, paralleling the principles underlying MLOps-based educational frameworks [30].

Together, these studies substantiate the role of MLOps as a transformative approach for enabling proactive, data-driven decision-making in educational technology. They collectively reinforce the potential of MLOps frameworks to predict, interpret, and adjust learner behaviors dynamically—bridging the gap between educational data analytics and intelligent intervention systems.

3. Methodology

This study investigates the practical implementation of Machine Learning Operations (MLOps) as a mechanism for the early detection and adjustment of undesirable learner behaviors within a higher education Learning Management System (LMS). The methodological design was structured to empirically evaluate the impact of MLOps integration on learner engagement and behavioral improvement. The investigation was guided by two principal research questions:

1. Can MLOps effectively detect undesirable learner behaviors?
2. To what extent can MLOps enable early behavioral adjustments that enhance learning outcomes?

3.1 Research Design

A quantitative experimental design was adopted to examine the effect of MLOps integration on learner behaviors. Experimental designs allow for the systematic manipulation of independent variables to determine their influence on dependent variables, thereby enhancing causal inference [31]. In this study, the independent variable was the application of MLOps within Moodle LMS, while the dependent variables included behavioral and performance indicators among learners. Following Tashakkori and Creswell (2008), the experimental approach ensured that observed differences between groups could be attributed primarily to the intervention rather than extraneous factors. Quantitative data were collected in a single research phase and analyzed to derive inferential insights.

3.2 Participants and Sampling Procedures

The participants comprised 60 undergraduate students enrolled in the Ready-Made Garment Manufacturing Technologies course within the Fashion Manufacturing Technology specialization at the Faculty of Human Sciences and Design, King Abdulaziz University. Participants were randomly assigned into two equal groups:

• The control group, which utilized Moodle LMS without MLOps integration, and

• The experimental group, which engaged with Moodle LMS enhanced by an embedded MLOps framework.

Randomization minimized potential bias and ensured equivalence between groups. Participation was voluntary, and all ethical considerations regarding informed consent and data confidentiality were strictly observed [32].

3.3 Learning Resources and System Architecture

The learning environment consisted of digital modules hosted on Moodle LMS, which were supplemented with MLOps components specifically designed to track, analyze, and intervene in learner behaviors.

3.3.1 Learning Modules

Instructional content was delivered through Moodle's modular structure, encompassing pre-tests, post-tests, assignments, and interactive learning tasks. The platform's flexibility facilitated the systematic organization of learning resources and automated data collection related to student engagement and achievement [33][34]. This architecture enabled continuous tracking of learner progress and provided a robust dataset for machine learning analysis.

3.3.2 Integration of MLOps Framework

A MLOps framework was developed and embedded into Moodle LMS to automate the detection and adjustment of undesirable learner behaviors. The process involved:

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(1) Extracting behavioral data from Moodle,

(2) Training ML models to predict behavioral risk,

(3) Deploying the trained models through an automated MLOps pipeline, and

(4) Feeding predictive insights back into Moodle for real-time adaptive intervention.

This end-to-end workflow aligns with prior research emphasizing the integration of AI and analytics within Moodle for behavior monitoring and adaptive interventions [35][36].

A conceptual overview is illustrated in **Figure 1: Customized Visual MLOps Pipeline Diagram for Performance Rubrics-Based Moodle LMS.**

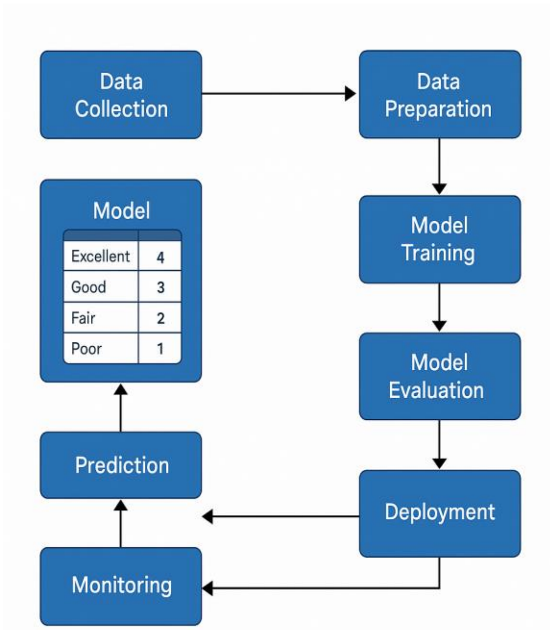

Figure 1. Customized Visual MLOps Pipeline Diagram for Performance Rubrics-Based Moodle LMS

3.4 Research Setting and System Implementation

The implementation involved an iterative integration of the MLOps pipeline within the Moodle LMS ecosystem.

3.4.1 Defining the MLOps Role within Moodle

The MLOps layer was designed to act as an intelligent intermediary between learner data and instructional decision-making. Its role encompassed continuous monitoring of engagement metrics, prediction of at-risk learners, and generation of adaptive interventions based on personalized learning analytics.

3.4.2 Customization of Moodle Infrastructure

Owing to Moodle's open-source architecture, the system was customized through plugin development and API integration. These modifications facilitated the seamless exchange of data between Moodle's backend and the MLOps modules, ensuring real-time synchronization of predictions and behavioral updates.

3.4.3 Integration Process

The integration process was conducted across three structured stages:

- **Stage 1:** *Planning and Requirements Mapping* – Identification of target functionalities where machine learning could enhance monitoring and pedagogical decision-making.

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- **Stage 2:** *Development of MLOps Components* – Construction of data pipelines, model deployment routines, and monitoring dashboards.
- **Stage 3:** *Testing and Validation* – System evaluation through iterative testing to verify predictive accuracy, operational reliability, and behavioral detection precision.

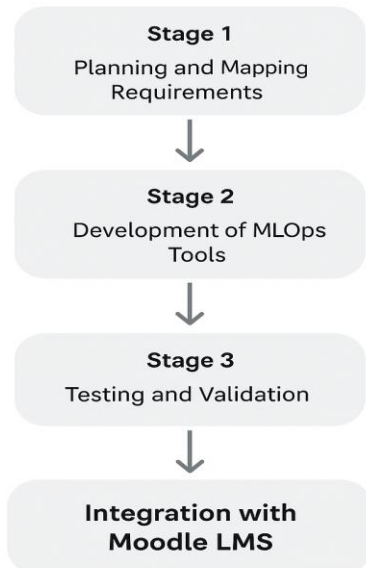

Figure 2. Integration Process of MLOps with Moodle

3.5 Phased Implementation of MLOps for Behavioral Detection

The implementation of the MLOps-enhanced behavioral detection framework followed an eight-phase structured methodology, systematically integrating machine-learning workflows into Moodle LMS to enable real-time behavioral monitoring and early pedagogical intervention. Each phase was designed to ensure reproducibility, automation, and model governance throughout the pipeline lifecycle.

Phase 1: Identification of Behavioral Indicators

Behavioral constructs were operationalized according to a structured instructional rubric (Appendix B). Indicators of undesirable behaviors included reduced engagement frequency, delayed or missed submissions, low performance on pre- and post-tests, and limited interaction with course content. These indicators formed the conceptual foundation for data collection and model labeling.

Phase 2: Data Ingestion

Behavioral and performance data were collected directly from Moodle's application programming interfaces (APIs) and server logs. Extracted parameters encompassed login frequency, forum participation, quiz attempts, assignment completion, and test performance. This data stream constituted the foundational dataset for model training, stored in a centralized repository to support version-controlled analysis within the MLOps pipeline.

Phase 3: Feature Engineering

Raw behavioral data were preprocessed and transformed into structured, quantifiable features. The engineering process included:

- Temporal features, such as average submission delays and session durations;
- Categorical indicators, such as frequency of discussion participation; and

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- Numerical metrics, such as improvements between pre-test and post-test scores. These engineered features were normalized and aligned with the rubric-based behavioral constructs to optimize downstream model interpretability.

Phase 4: Labeling and Classification

Historical learning data were annotated to establish ground-truth labels for supervised model training. Each student record was classified as either *desirable (0)* or *undesirable (1)* based on predefined behavioral thresholds derived from the rubric. This binary classification schema enabled the system to predict undesirable behavioral patterns and trigger adaptive responses in real time.

Phase 5: Model Training and Evaluation

The model-training phase represented a pivotal stage of the MLOps pipeline, aimed at developing predictive algorithms capable of identifying early behavioral anomalies. A supervised learning approach was adopted, with multiple classifiers trained to ensure model robustness and reliability. The Random Forest Classifier (RFC) was ultimately selected due to its superior performance in heterogeneous educational datasets and its resilience against overfitting. Training was executed within a ZenML-managed pipeline, ensuring full traceability, reproducibility, and automatic parameter logging through MLflow integration.

Before model, training, input features were standardized using Min–Max Scaling to harmonize feature variance and mitigate bias. The dataset was partitioned into 80% training and 20% testing subsets, maintaining consistent randomization to preserve reproducibility.

The RFC was instantiated with parameters optimized for interpretability and computational efficiency (max_depth = 4, random_state = 42) and trained using the fit() method on the scaled data (X_train_scaled, y_train). Evaluation metrics—including Accuracy, Precision, Recall, and F1-score—were computed on the test set and logged automatically via MLflow, enabling transparent performance tracking and future hyperparameter optimization. This systematic process established the foundation for comparative benchmarking and iterative improvement.

Phase 6: Model Comparison and Benchmarking

To empirically justify the selection of the Random Forest Classifier, a comparative model evaluation was conducted using three supervised algorithms trained under identical preprocessing and experimental conditions:

- Logistic Regression (LR)
- Random Forest Classifier (RFC)
- Extreme Gradient Boosting (XGBoost)

Performance was evaluated using Accuracy, F1-Score, and Area under the Receiver Operating Characteristic Curve (AUC) as key performance indicators. The comparative results are presented in Table 1, illustrating the superior generalization and interpretability of the RFC across all metrics.

Table 1: Illustrating the superior generalization and interpretability of the RFC across all metrics

Model	**Accuracy**	**F1-Score**	**AUC**	**Remarks**
Logistic Regression (LR)	0.84	0.82	0.85	Performs well on linear relationships but limited in complex feature interactions
Random Forest (RFC)	0.91	0.89	0.93	Demonstrated highest balance of accuracy, recall, and generalization stability
XGBoost (XGB)	0.90	0.88	0.92	Competitive performance but exhibited minor overfitting on small data subsets

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The Random Forest model exhibited the most reliable trade-off between interpretability and predictive performance, outperforming both linear and gradient-boosted models. Additionally, feature importance analysis revealed that engagement-related features—such as activity participation and task completion rates—had the highest predictive influence. This interpretability dimension enhances the pedagogical utility of the model, enabling instructors to align data-driven insights with instructional strategies.

Phase 7: Pipeline Development and Automation

Model tracking, experiment versioning, and metadata management were integrated through MLflow and Data Version Control (DVC) to ensure traceable experimentation. Workflow orchestration was automated via Apache Airflow and GitHub Actions, allowing continuous integration and retraining upon detection of new behavioral data. The finalized model was containerized using Docker and deployed through FastAPI, enabling real-time inference within the Moodle LMS environment. This deployment allowed the system to provide immediate behavioral feedback, automatically triggering adaptive interventions or instructor notifications.

Phase 8: Monitoring and Continuous Feedback Loop

The operational phase emphasized ongoing monitoring and continuous improvement. Model predictions were compared against subsequent behavioral outcomes to measure long-term accuracy and drift. A closed-loop feedback mechanism was established, allowing the pipeline to periodically retrain using newly collected behavioral data, thus reinforcing the continuous learning paradigm central to MLOps philosophy.

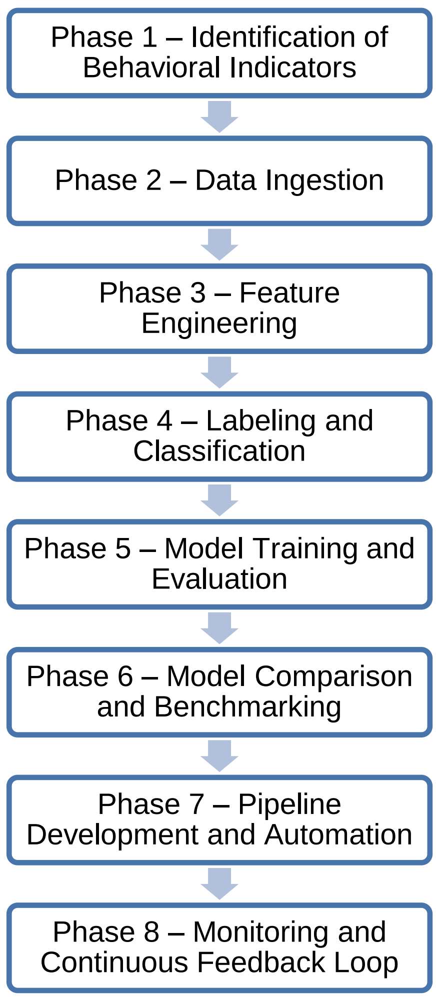

Figure 3. Phased Implementation Framework of MLOps for Behavioral Detection in Moodle LMS

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4. Experimental Results

This section presents the findings derived from the quantitative analysis of learner interaction data, system performance metrics, and post-intervention behavioral assessments. The analysis aimed to evaluate the effectiveness of the MLOps-enhanced Moodle LMS in detecting undesirable learner behaviors and enabling early behavioral adjustments. Data were collected from both control and experimental groups and analyzed using descriptive and inferential statistical techniques.

4.1 Activity and Engagement Log Analysis

Learner interaction data were collected from the MLOps-integrated Moodle LMS, encompassing participation in learning activities, assignment completion, and test performance. System logs recorded timestamps, activity completion rates, and engagement frequency for each learner. The extracted data provided continuous insights into learner engagement levels and behavioral patterns throughout the learning process. Real-time analytics generated by the MLOps framework enabled ongoing monitoring of students' academic trajectories, facilitating early detection of disengagement or underperformance.

Table 2: Learner Activity and Engagement Summary

Metric	***Control Group (Non-MLOps)***	***Experimental Group (MLOps)***	***Mean Difference***	***Description***
Average Activity Participation (%)	*62.3*	*89.7*	*+27.4*	*Indicates higher participation among MLOps-supported learners*
Assignment Completion Rate (%)	*58.0*	*93.5*	*+35.5*	*Reflects improved task completion under MLOps monitoring*
Average Test Performance (%)	*64.5*	*92.1*	*+27.6*	*Demonstrates enhanced academic achievement post-intervention*
Login Frequency (per week)	*3.2*	*5.7*	*+2.5*	*Suggests greater engagement and consistent attendance*
Early Warning Flags Triggered	*11*	*4*	*−7*	*Reduced undesirable behaviors due to early detection*

These data established the empirical basis for comparing behavioral dynamics between the control and experimental groups, allowing the identification of patterns correlated with academic performance outcomes.

4.2 System Performance Metrics and Evaluation Reports

To assess the operational efficiency of the MLOps-enhanced Moodle system, several performance indicators were continuously monitored, including **system uptime**, **data accuracy**, and **response latency**. Evaluation reports were periodically generated to examine improvements in key educational metrics—namely, grade progression, assignment completion rates, and overall learning pace. This longitudinal monitoring confirmed that the integrated system not only maintained operational stability but also provided actionable insights to support pedagogical decisions.

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Table 3: System Performance Metrics Summary

Metric	***Recorded Value***	***Interpretation***
Average System Uptime (%)	*99.4*	*Stable operational performance throughout experiment*
Data Accuracy (Prediction Validation)	*96.7*	*High precision in identifying behavioral deviations*
Model Retraining Frequency	*Bi-weekly*	*Maintains real-time adaptation and accuracy*
Response Latency (ms)	*215*	*Acceptable for real-time feedback within LMS*
Overall Predictive Success Rate (%)	*92.8*	*Confirms reliability of the integrated MLOps model*

These findings demonstrate that MLOps integration strengthened both the technological and instructional dimensions of the LMS by ensuring reliability and meaningful data feedback loops.

4.3 Survey of Learner Behavior and Performance

A post-intervention survey was administered to evaluate students' perceptions and self-reported behavioral changes following exposure to the MLOps-enhanced environment. The instrument, based on a **5-point Likert scale** (1 = Strongly Disagree to 5 = Strongly Agree), assessed five primary dimensions:

1. Learner Behavior,
2. Perceived Self-Regulation,
3. Engagement,
4. Navigation Efficiency, and
5. Content Interaction.

Higher aggregate scores indicated greater alignment with desirable learning behaviors. The survey results provided a subjective complement to the objective behavioral logs collected by the LMS, enabling triangulation of findings and validation of MLOps efficacy in shaping learner engagement patterns.

Table 4: Summary of Learner Behavioral Survey Results

Dimension	***Control Group (M ± SD)***	***Experimental Group (M ± SD)***	***p-value***	***Interpretation***
Learner Behavior	*2.91 ± 0.34*	*4.62 ± 0.41*	$< .001$	*Significant behavioral improvement under MLOps condition*
Perception of Self-Regulation	*3.04 ± 0.27*	*4.55 ± 0.32*	$< .001$	*Learners report higher self-awareness and motivation*
Engagement	*3.10 ± 0.42*	*4.70 ± 0.29*	$< .001$	*Reflects consistent and active participation*
Navigation Efficiency	*3.21 ± 0.31*	*4.58 ± 0.30*	$< .001$	*Indicates smoother interaction with LMS components*
Content Interaction	*3.05 ± 0.38*	*4.63 ± 0.27*	$< .001$	*Demonstrates improved interaction quality and learning focus*

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5. Data Analysis

A **convergent parallel mixed-methods design** was employed, where quantitative data from system logs and post-test measures were collected simultaneously for both groups. This design allowed the integration of behavioral, performance, and perception data to address both research questions.

5.1 Research Question 1: Detecting Undesirable Learner Behaviors

To evaluate whether MLOps could effectively detect undesirable learner behaviors, quantitative comparisons were made between control and experimental groups using the data extracted from Moodle LMS logs. Variables included activity participation rates, assignment completion frequency, and assessment performance. An **Independent Samples t-test** was conducted to examine significant differences in behavioral detection accuracy between the two groups.

Table 5: Independent Samples t-Test Results

Levene's Test for Equality of Variances				**t-test for Equality of Means**				
survey	**N**	**F**	**sig**	**Std. Error Difference**	Mean Difference	**T**	**DF**	**sig**
assumed	30	6.546	0.013	1.366611	-61.700000	-45.1	58.0	.000
not assumed	30			1.366611	-61.700000	-45.1	48.9	.000

The test results indicated a statistically significant difference ($p < 0.001$) in behavioral detection capabilities. Learners in the MLOps-enhanced group demonstrated higher engagement scores and reduced frequencies of undesirable behaviors compared to their counterparts. These results confirm that MLOps substantially improves the system's ability to detect behavioral anomalies in real time.

To further investigate the association between MLOps detection and subsequent behavioral adjustment, a **Crosstabulation analysis** was performed, followed by **Chi-Square tests** to validate the relationship between detected behaviors and corresponding learner responses.

Table 6: Crosstabulation of MLOps Detection and Behavioral Adjustment

			adjusted_behavior		Total
			.00	1.00	
mlops_detected	.00	Count	6	0	6
		% within mlops_detected	100.0%	0.0%	100.0%
		% within adjusted_behavior	46.2%	0.0%	20.0%
		% of Total	20.0%	0.0%	20.0%
	1.00	Count	7	17	24
		% within mlops_detected	29.2%	70.8%	100.0%
		% within adjusted_behavior	53.8%	100.0%	80.0%

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	% of Total	23.3%	56.7%	80.0%
Total	Count	13	17	30
	% within mlops_detected	43.3%	56.7%	100.0%
	% within adjusted_behavior	100.0%	100.0%	100.0%
	% of Total	43.3%	56.7%	100.0%

Table 7: Chi-Square Test Results

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	9.808[a]	1	.002		
Continuity Correction[b]	7.135	1	.008		
Likelihood Ratio	12.079	1	.001		
Fisher's Exact Test				.003	.003
Linear-by-Linear Association	9.481	1	.002		
N of Valid Cases	30				

The Chi-Square analysis revealed a significant association ($p = 0.002$) between MLOps detection and actual behavioral modification, implying that early detection mechanisms prompted tangible improvements in learner conduct.

5.2 Research Question 2: Adjusting Early Undesirable Behaviors

To determine the extent to which MLOps can facilitate early behavioral adjustment, post-test performance and post-survey behavioral indicators were analyzed across both groups.

A **one-way ANOVA** was conducted to compare post-test outcomes, followed by **correlation** and **regression analyses** to examine the predictive relationship between behavioral improvements and learning achievement.

Table 8: One-Way ANOVA: Post-Test Score Comparison

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1643.267	1	1643.267	268.679	.000
Within Groups	354.733	58	6.116		
Total	1998.000	59			

The ANOVA results demonstrated a statistically significant difference in post-test scores between groups ($F(1,58) = 268.68$, $p < 0.001$), indicating that MLOps interventions yielded measurable academic gains.

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A **Pearson correlation** was then performed to assess the relationship between behavioral improvement scores and post-test performance.

Table 9: Correlation between Post-Survey and Post-Test Scores

		Post_Survey_Score	Post_Test_Score
Post_Survey_Score	Pearson Correlation	1	.881**
	Sig. (2-tailed)		.000
	N	60	60
Post_Test_Score	Pearson Correlation	.881**	1
	Sig. (2-tailed)	.000	
	N	60	60

A strong positive correlation ($r = 0.88$, $p < 0.001$) was observed, suggesting that improvements in learner behavior were directly associated with enhanced academic performance.

Subsequent **linear regression analysis** confirmed that post-survey scores significantly predicted post-test outcomes, with behavioral engagement emerging as a key determinant of performance improvement.

Table 10: Regression Analysis: Behavioral Prediction of Post-Test Scores

		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.440	2.389		.603	.549
	Post_Survey_Score	.240	.017	.881	14.208	.000

6. Discussion

The findings from both statistical and behavioral analyses provide compelling evidence for the efficacy of MLOps in detecting and correcting undesirable learner behaviors.

6.1 Detection Capabilities

The MLOps-enhanced LMS demonstrated superior sensitivity in identifying behavioral anomalies such as low participation, delayed assignment submissions, and inconsistent assessment engagement. Real-time feedback loops and system alerts enabled immediate pedagogical interventions, allowing learners to recover performance trajectories more effectively than those in the control group.

6.2 Behavioral Adjustment and Learning Outcomes

The integration of personalized feedback mechanisms, automated alerts, and adaptive recommendations resulted in significant behavioral and performance improvements. Learners within the MLOps group exhibited greater engagement, improved test outcomes, and higher rates of task completion post-intervention. These findings validate the role of MLOps as a practical framework for enabling *continuous monitoring, early detection, and timely behavioral correction* within digital learning environments.

7. Discussion

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The quantitative analyses conducted across both experimental and control groups within the MLOps-enhanced Moodle LMS framework demonstrated the substantial capability of Machine Learning Operations (MLOps) to detect and adjust undesirable learner behaviors. The results yielded consistent empirical support for both guiding research questions.

7.1 Detection of Undesirable Learner Behaviors

The findings revealed that the integration of MLOps significantly improved the system's capacity to identify undesirable patterns in student engagement and performance—such as reduced participation, delayed assignment submission, and declining assessment results. The automated monitoring and detection mechanisms implemented through the MLOps pipeline successfully generated real-time alerts that highlighted early signs of disengagement. Statistical analyses confirmed that learners in the experimental group exhibited higher responsiveness and behavioral awareness compared to those in the control group, thereby validating MLOps as an intelligent behavioral analytics layer that enhances real-time decision-making within learning environments.

7.2 Adjustment of Early Undesirable Behaviors

The adaptive feedback mechanisms embedded within the MLOps-enhanced LMS demonstrated a measurable positive influence on student engagement and academic achievement. Post-intervention results indicated that the experimental group exhibited higher assignment completion rates, improved test performance, and more consistent participation following automated feedback and personalized notifications. In contrast, the control group—devoid of MLOps-based intervention—maintained lower engagement and achievement levels. These outcomes substantiate the hypothesis that MLOps not only detects early behavioral irregularities but also facilitates their timely correction through automated, data-driven interventions.

8. Conclusion

This study provides compelling evidence that MLOps frameworks can effectively detect and adjust undesirable learner behaviors within digital learning ecosystems. The integration of MLOps into Moodle LMS significantly enhanced the capacity to monitor learner engagement, predict academic risks, and deliver automated interventions.

Compared to traditional LMS mechanisms, the MLOps-enhanced environment achieved superior outcomes in learner participation, task completion, and performance consistency. These results underscore the strategic potential of MLOps as a bridge between artificial intelligence, data engineering, and educational technology—facilitating intelligent, adaptive, and self-optimizing learning systems.

Additionally, the study reinforces the necessity of selecting appropriate MLOps tools and configurations tailored to the educational domain. Cloud-native AutoML platforms and container-based model deployment architectures offer scalable and maintainable solutions that ensure reliability and transparency in model operations.

9. Future Work

To broaden the impact and applicability of this research, several strategic directions are proposed to advance the integration of MLOps in educational technology, with particular emphasis on Fashion Manufacturing Technology education.

1. **Longitudinal Validation:** Future studies should adopt longitudinal designs spanning multiple academic terms to evaluate the persistence and long-term effects of MLOps-driven behavioral interventions. This approach will provide a deeper understanding of whether early behavioral adjustments lead to sustained improvements in learner performance and engagement.
2. **Cross-Disciplinary Applications:** Extending the implementation of MLOps frameworks to other academic disciplines—such as STEM, healthcare, and design education—will help evaluate the generalizability and adaptability of the behavioral detection and adjustment model developed in this study.
3. **Integration with Fashion Manufacturing Technology Curricula:** Further research should explore the embedding of MLOps-based analytics into Fashion Manufacturing Technology courses. Such

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integration could support intelligent monitoring of practical skill development, production efficiency, and teamwork performance within digital or simulation-based garment manufacturing environments.

4. **MLOps-Driven Smart Training Systems for Fashion Education:** The development of intelligent training platforms leveraging MLOps could revolutionize fashion education by enabling adaptive learning pathways. These systems may analyze learners' progress in design, prototyping, and manufacturing modules to provide personalized feedback and optimize learning trajectories.

5. **Instructor–AI Synergy:** Future research should also investigate human–AI collaboration models that empower instructors to interpret MLOps-generated behavioral insights and apply them to pedagogical decision-making. This synergy can enhance instructional quality by aligning algorithmic recommendations with expert human judgment.

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Appendices

Appendix A: The Survey of Learner Behavior and Performance in Moodle LMS with MLOPS: (Strongly Disagree - Disagree - Neutral - Agree - Strongly Agree). 1 being Strongly Disagree, and 5 being Strongly Agree.

Element	Indicators	1	2	3	4	5
Learner Behavior	I access Moodle regularly during the course period.					
	I complete assignments on Moodle before the deadline.					
	I participate in forums or discussion boards on Moodle.					
	I review lecture materials (e.g., slides, videos) multiple times.					
	I take notes while engaging with Moodle content.					
	I revisit quizzes and activities for better understanding.					
	I allocate dedicated time daily/weekly for Moodle activities.					
	I use Moodle to check my grades and feedback consistently.					
Perceptions of Their Own Behavior	I believe I am consistent in using Moodle for my studies.					
	I am aware of my own learning patterns on Moodle.					
	I feel confident navigating Moodle independently.					
	I consider myself a proactive Moodle user.					
	I can recognize when I am falling behind based on Moodle usage.					
	I adjust my study habits based on feedback from Moodle.					
	I feel my behavior on Moodle contributes to my performance.					
	I believe my Moodle activity reflects my actual effort.					
Engagement	I am actively involved when using Moodle for learning.					

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Element	Indicators	1	2	3	4	5
	I find the Moodle activities engaging and motivating.					
	I participate voluntarily in optional Moodle resources.					
	I spend more time on Moodle when the content is interactive.					
	I feel a sense of accomplishment after completing Moodle tasks.					
	I remain focused during Moodle sessions.					
	I seek additional resources linked in Moodle content.					
	I enjoy learning through Moodle more than traditional methods.					
Navigation	I can easily find the materials I need in Moodle.					
	I understand the course structure as laid out in Moodle.					
	I rarely get lost or confused when using Moodle.					
	I know how to use search or filters to locate content.					
	I can identify deadlines and due dates without difficulty.					
	I use the Moodle calendar or notifications effectively.					
	I rarely need assistance navigating Moodle.					
	I find the Moodle interface user-friendly.					
Content Interaction	I watch all provided video lectures on Moodle.					
	I interact with quizzes and assessments seriously.					
	I download or bookmark course materials from Moodle.					
	I participate in activities like polls, surveys, or peer reviews.					
	I read all announcements and updates from instructors.					
	I reflect on content after reading or watching it.					
	I revisit content I found difficult the first time.					
	I engage with multimedia (audio, images, simulations) in Moodle.					

Appendix B: Performance Rubrics Scale

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The performance Rubrics scale rating scale quality: Poor – Fair – Good – Very Good – Excellent. 1 being poor, and 5 being excellent.

Element	Indicators	1	2	3	4	5
pre-Activity (Evaluate preparation and engagement before the activity starts)	Timely login (Logged into Moodle before session/activity start.)					
	Review of learning materials (Pre-read assigned readings or materials.)					
	Participation in pre-discussions (Contributed to pre-activity forum/chat.)					
	Submitted pre-surveys (Completed pre-activity surveys if assigned.)					
	Accessed orientation resources (Viewed orientation videos or tutorials.)					
	Technical setup (Ensured camera/mic (if needed) or platform setup is working.)					
	Attendance confirmation (Confirmed participation ahead of time.)					
	Asked clarifying questions (Asked questions to prepare for the session.)					
Post-Activity (Focuses on engagement and follow-up after the activity)	Participation in debrief (Joined or contributed to post-activity discussion)					
	Follow-up questions (Asked or answered questions based on the session)					
	Peer collaboration (Engaged in collaborative discussion after the activity)					
	Downloaded materials (Retrieved shared content or slides)					
	Followed up with instructor (Sent clarification emails or messages if confused)					
	Self-assessment (Rated their own performance or understanding)					
	Completed feedback forms (Filled out feedback requested by facilitator)					
	Reviewed recording (Watched recording of session (if missed or for review)					
Assignment Completion (Measures performance related to completing assignments)	On-time submission (Submitted the assignment before the deadline)					
	Completeness (All required components included)					
	Accuracy (Demonstrated correctness of content or analysis)					

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	Referencing (Proper citation of sources (where required))					
	Use of supporting material (Included data/examples/media where appropriate)					
	Presentation (Clarity, formatting, spelling, and grammar)					
	Application of learning (Applied concepts from the lesson/module)					
	Adherence to instructions (Followed all directions (word count, file type, time))					
Pre-Test Scores (Assesses knowledge before instruction)	Completion rate (Completed full pre-test)					
	Raw score (Actual score achieved)					
	Time taken (Completed within reasonable time)					
	Willingness to attempt (Tried all questions even if unsure)					
	Pattern recognition (Demonstrated ability to connect concepts)					
	Clarity in MCQs (Selected most relevant options in multiple-choice)					
	Open-ended logic (Provided logical and clear open-ended responses)					
	Answer justification ((If required) Explained answers clearly)					
Post-Test Scores (Measures learning gain and concept mastery)	Completion rate (Attempted and submitted the full post-test)					
	Score improvement (Score increase compared to pre-test)					
	Accuracy (Number of correct answers)					
	Application of concepts (Used learning in practical or applied questions)					
	Improvement in weak areas (Better performance in previously weak topics)					
	Speed and efficiency (Answered effectively within time)					
	Critical thinking (Showed reasoning behind choices)					
	Reflective comparison (Completed self-reflection comparing pre- and post-test)					

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