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Research Article

Analysis of Academic Performance using Learning Management System (LMS) Data and Bayesian Network

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ABSTRACT

Learning Management Systems (LMS) have become integral tools in higher education, generating vast amounts of data that can be leveraged to analyze and enhance academic performance. Despite the abundance of this data, effectively harnessing it to understand complex relationships between learning activities and student outcomes remains a challenge. This paper explores the application of Bayesian Network (BN), a powerful technique in Educational Data Mining (EDM) to model and predict student outcomes using LMS data. BN provides a probabilistic framework to explore how various learning analytics variables influence academic success. Using LMS data from an online undergraduate Mathematics course, the model investigated the impact of student engagement, resource utilization, and participation on exam grades. The results show that consistent attendance (88%), active participation in lecturing sessions (85%), and involvement in online mathematical laboratory activities (62%), despite lower engagement in other areas such as assessments and gamification, are strongly associated with favourable final exam outcomes (62% achieving 'Good' or 'Excellent' grades). Numerical simulations were conducted to explore future student outcomes by manipulating key variables, demonstrating the potential of improved learning strategies such as full participation, improved prior knowledge and complete utilization of digital resources. This study highlights the utility of BN in analyzing LMS data to inform educational practices and ultimately enhance academic performance in higher education.

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1. INTRODUCTION

E-learning systems have fundamentally reshaped higher education by delivering remote education and fostering interactive, personalized learning experiences through sophisticated online technologies. Learning Management Systems (LMS) including platforms such as Moodle, Canvas, and Blackboard are central to this transformation, functioning not only as repositories for educational content but also as dynamic data ecosystems. The LMS, also referred to as a Course Management System (CMS) or Virtual Learning Environment (VLE), has evolved over decades to become a cornerstone of institutional instructional technology infrastructure. Defined as a server-based or cloud-based software program containing user, course, and content information, the LMS provides a dedicated place to learn and teach independent of time and space boundaries (Sharma & Vatta, 2013). These platforms facilitate the distribution of lecture materials, enable online assessments, and support communication between students and instructors. Engagement within these platforms, particularly through quality online interactions, strongly relates to both academic success and students' satisfaction with their courses (Naveh et al., 2012). Several LMS platforms have begun integrating generative Artificial Intelligence (AI), offering AI-driven tools such as plugins for dynamic content creation and AI-driven assessments to provide real time insights that enhance the learning experience (Alier et al., 2025). This proliferation of e-learning platforms has generated a wealth of multifaceted student data within LMS. This data includes demographics, academic performance, registration details, and access logs. These data, now readily accessible in real-time due to technological advancements, form a comprehensive digital footprint of student learning, offering unprecedented opportunities for analysis and intervention.

Consequently, institutions of higher education are increasingly employing learning analytics (LA) to glean actionable insights from these digital traces. LA involves the systematic collection, analysis, and interpretation of student data, aiming to uncover hidden patterns, forecast academic outcomes, and tailor educational experiences to individual needs (Siemens & Long, 2011). This process empowers educators to optimize curriculum design and instructional methodologies by scrutinizing engagement metrics (Shaun et al., 2014). Most importantly, LA facilitates the growth of students into self-regulated learners by enabling them to better monitor their progress, identify areas for improvement, and adjust their learning strategies accordingly (Kleimola et al., 2025). At the institution level, LA equips institutions with data informed intelligence for strategic decision making, providing insights into student success and resource allocation (Daniel, 2015), as well as enhancing institutional decision-making (Baker, 2010). Current digital technologies, particularly within Artificial Intelligence in Education (AIED) enable the collection of fine-grained data on LA for simulating and predicting learning processes and behaviors. This information can inform actions for a wide range of stakeholders, including students, teachers, curriculum designers and managers (Rienties et al., 2020).

Several key indicators derived from LMS data have been identified as pivotal in predicting and enhancing student performance. The collection of essential LMS metrics typically commences with student activity logs, which encompass low-level operational metrics like log-in frequency, time spent on specific tasks, and assignment completion rates (Pérez-Suay et al., 2024; Conijn et al., 2016). These logs are critical for assessing self-discipline and persistence. Next, engagement patterns are vital, reflecting the depth and quality of cognitive interaction with the course material. This engagement is measured by specific interactions such as clicks, time spent on tasks, and active participation in discussions (Qazdar et al., 2023; Suwawi et al., 2021; Mužinić et al., 2024). Assessment and grades are integrated to provide direct measurements of achieved learning outcomes. These grades cover, for example, both in-between assessment results and final marks (Conijn et al., 2016; Riestra-González et al., 2021; Maraza-Quispe et al., 2021). Finally, broader behavioral indicators are considered, which include dimensions such as overall academic performance, access frequency, homework completion, social interactions, and quiz participation (Suwawi et al., 2021; Maraza-Quispe et al., 2021).

To effectively process and interpret the large volume of educational data, institutions are increasingly adopting advanced statistical techniques and data mining (DM) tools. Educational Data Mining (EDM), a specialized branch of DM and machine learning, focuses on developing methods to extract knowledge from educational environments (Romero & Ventura, 2010). This field leverages computational approaches to discover patterns and relationships that are not immediately apparent, thereby providing a deeper understanding of student learning processes (Baker, 2010). EDM utilizes a diverse range of machine learning techniques, including decision trees, Naïve Bayes, and K-nearest neighbors, to discover association rules, classifications, and clusters within educational datasets (Namoun & Alshanqiti, 2021; Luan & Tsai, 2021; Rizwan et al., 2025). For instance, Suwawi et al. (2021) used Naïve Bayes to classify student performance into three categories – good, satisfactory, and poor based on the LMS activity log. Similarly, Mužinić et al. (2024) utilized various machine learning algorithms (e.g. Random Forest, Decision Tree, and Gradient Boosting classifier) to analyze LMS data and predicting final grades within the Moodle environment. Riestra-González et al. (2021) utilized machine learning to create models for the early prediction of students' performance in solving LMS assignments by just analyzing the LMS log files generated up to the moment of prediction. In a study by Aljaloud et al. (2022), they explored the application of CNN-LSTM models, demonstrating their effectiveness in capturing spatial and temporal dependencies within student interaction logs. In the domain of Learning Analytics Interventions (LAI), Alalawi et al. (2025) proposed an integration of LA and pedagogical approaches framework, which enables academics to develop course specific predictive models based on historical course assessment data. Furthermore, building on the increasing prominence of AI, Shoaib et al. (2024) proposed an AI-driven Student Success Predictor that integrates data from multiple sources and uses advanced machine learning techniques such as CNN, Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN) and Bayesian averaging to predict student grades, retention, and dropout risk.

In recent approaches, big data technologies and machine learning tools have been utilized to enable the processing and analysis of large scale LMS datasets, supporting more robust and scalable EDM applications (Elfeky et al., 2024; Cantabella et al., 2019; Fan, 2024). For instance, Cantabella et al. (2019) proposed big data technologies to analyze 70GB student behavior database which aiming to improve student performance by enhancing the learning process. In another work, Fan (2024) utilized Apache Hadoop, a robust big data tool to facilitate the efficient storage and analysis of large datasets. A Feed Forward Neural Network (FNN) model is then developed to identify distinctive patterns related to student success. The authors show that this approach enhances the precision of execution computations and timely interventions by teachers, parents, and administration, resulting in a more efficient student management system. These studies underscore the diverse and effective application of predictive modeling in educational data mining to enhance student outcomes.

Although machine learning predictive analysis has been widely adopted, causal learning analysis is attracting increasing attention for its ability to elucidate complex relationships in LMS data. For example, Local Causal Learning Algorithms such as Hybrid Efficient Identification of Subsets Algorithm (HEISA) and Efficient Local Causal Structure Learning (ELCS) efficiently identify direct causes and effects related to specific target variables (e.g., student success) by using feature selection and Markov Blanket discovery techniques (de Carvalho & Zárate, 2020; Yang et al., 2021; Wu et al., 2024; Cheng et al., 2024). A different strategy implemented by Guo et al. (2024), starts by learning local causal structures around individual attributes by identifying their direct causes and effects within LMS data, and then combines them to build a global causal network. More advanced algorithms use techniques like reproducing kernel Hilbert space and gradient-based optimization to handle real world LMS data complexities, such as temporal changes in student behavior or nonlinear effects of learning activities (Wu et al., 2024; You et al., 2024).

While many of these EDM algorithms are effective at prediction, a significant challenge lies in the inherent complexity and high dimensionality of educational datasets. For example, many machine learning models, often termed "black box" approaches, lack the interpretability necessary to provide actionable insights for pedagogical improvements (Rosé et al., 2019). The resulting predictions, without transparent reasoning, limit the ability of educators to precisely identify key influencing factors, achieve sufficient predictive accuracy, and design targeted interventions. To bridge this gap, a causal modeling approach is necessary to move beyond simple prediction and establish the dependencies between specific learning activities and student outcomes.

In this paper, the application of EDM, specifically Bayesian Network (BN) is explored to analyze academic performance using LMS data. BN provide a probabilistic framework for modeling complex relationships between variables, allowing for the prediction of student outcomes and the identification of factors influencing academic success. Unlike local methods that focus on a single outcome, BNs model the joint causal relationships among all variables in the system simultaneously. This enables BNs to support global inference, simulate multi-variable interventions, and represent complex feedback loops and dependencies across the entire learning environment. Furthermore, recent advances in efficient BN learning algorithms have improved their applicability to large scale LMS datasets by reducing computational complexity while preserving accuracy in causal discovery (Minn & Shunkai, 2023). Such a system wide causal understanding is essential for designing personalized interventions tailored to individual learners, ultimately enhancing learning outcomes and improving student success rates (Chen et al., 2019).

Therefore, this study aims to build a BN model that leverages LA to capture these relationships and better predict student outcomes. The remainder of this paper is organized as follows. Section 2 introduces the BN method. In Section 3, the results and discussion of the numerical experiment are presented. The conclusions are provided in Section 4.

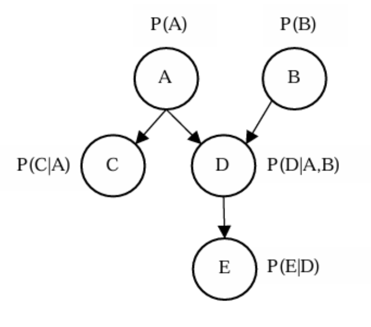
2. METHODOLOGY

This study utilizes BN, a probabilistic model known for their flexible representation and clear interpretability, to model the data (Pearl, 1988). A BN represents the joint probability distribution of discrete variables through a directed acyclic graph (DAG), where nodes signify random variables and edges indicate conditional dependencies (Koller & Friedman, 2009; Jensen & Nielsen, 2007). Nodes are categorized as parent (causes) or child (consequences), with root nodes having no parents. Variables can be either discrete (finite states) or continuous (infinite values). The directional edges, representing causal influences, are quantified by conditional probability values stored in Conditional Probability Tables (CPTs) for discrete variables. Given the independencies inherent in the network structure, the joint distribution of all variables is equivalent to the product of the conditional distributions associated with each node, such that

$$\mathrm{P}(\mathrm{X}_1, \mathrm{X}_2, \ldots, \mathrm{X}_\mathrm{n}) = \prod_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{P}\big(\mathrm{X}_\mathrm{i} | \mathrm{Pa}(\mathrm{X}_\mathrm{i})\big) \tag{1}$$

where $X_i = \{X_1, X_2, \ldots, X_n\}$ represents the set of all possible values of variable X_i. If the value of a variable X_i need to be predicted, and the values of a set of variables X_e are known, the probability of each possible value of X_i can be calculated given each possible configuration of X_e. This probability distribution can be obtained from the joint distribution in Eq. (1). However, computing the full joint distribution is not necessary because efficient algorithms exist that calculate $P(X_i|P_e)$ by using the factorisation of the joint distribution imposed by the network structure (Shenov & Shafer, 1990). A typical BN structure is depicted in Figure 1, where nodes are random variables and links represent their dependencies. A sample CPT for node D is shown, using abstract labels A_i, B_i, and D_i to represent possible states of nodes A, B, and D for illustrative purposes.

Designing a BN comprises three main stages: variable structuring, parameter estimation, and inference. Variable structuring involves identifying variables and their causal relationships. This can be done either through expert-driven approaches, where domain specialists manually define the network based on their knowledge (Russell & Norvig, 2020), or through algorithmic methods, where it infers the structure from data (Murphy, 2002). Once the structure is defined, parameter estimation involves determining prior probabilities and CPT values. This can be achieved using exact data through methods like Maximum Likelihood Estimation and Bayesian Estimation, or through expert elicitation when data is scarce (Jensen & Nielsen, 2007). The final step is inference, where variable probabilities are updated with new evidence. Node values are then estimated throughout the network using algorithms like loopy belief propagation and Bayes' theorem, which follow the network's links. In terms of evaluation, BNs-based models are frequently compared with other machine learning techniques such as neural networks and logistic regression, often demonstrating competitive or superior performance in educational settings (Wong et al., 2004, Käser et al., 2017). These methods collectively advance the application of BNs in modeling complex learning processes and improving educational outcomes.



Node	Condition		Conditional probability	
D	A	B	D=D1	D=D2
	A1	B1	0.3	0.7
	A1	B2	0.2	0.8
	A2	B1	0.5	0.5
	A2	B2	0.1	0.9

Figure 1. A Bayesian Network (BN) graphically represents probabilistic dependencies between variables, and the Conditional Probability Table (CPT) quantifies these relationships for the node D, conditioned on its parents.

BNs are increasingly being utilized in LMS to model and predict students' learning processes. These networks provide a structured way to analyze educational data, offering insights into students' learning states and potential outcomes. Key applications of the BN include modeling learning processes by analyzing LMS log data, enabling the estimation and prediction of students' learning states. This facilitates targeted support and interventions (Kondo & Hatanaka, 2018; Kondo & Hatanaka, 2019). Specifically, Kondo and Hatanaka (2018) demonstrated the use of BNs to analyze LMS log data for predicting student learning progress. Their model analyzed various student activity variables to predict academic outcomes, enabling early interventions for at-risk students. Their subsequent work in 2019 further improved the accuracy of these predictions by incorporating more complex behavioral variables, resulting in more refined learning pattern identification and targeted interventions. Moreover, numerous educational assessment systems utilize BNs. As highlighted by Culbertson (2016), such systems have been identified as empirical examples demonstrating the application of BNs across diverse educational domains.

A common issue in educational settings is incomplete data, where uncertainty and missing values are prevalent. BNs are well-suited to handle this, as they support decision making under uncertainty through the representation of conditional probabilities (Heckerman, 1998; Ellis et al., 2008). This is particularly valuable because educational datasets often suffer from missing values due to various factors, such as students skipping assignments, technical glitches in data collection, or inconsistent data entry. BNs encode probabilistic relationships, allowing for robust modeling even when some data entries are missing or uncertain. Furthermore, recent advances in efficient BN learning algorithms have improved their applicability to large scale LMS datasets by reducing computational complexity while preserving accuracy in causal discovery (Minn & Shunkai, 2023).

The inference mechanism in a BN provides a significant advantage for causal inference and prediction by enabling the learning and representation of complex causal relationships within data. BNs facilitate simulating the effects of different educational strategies, thereby aiding decision making and personalized intervention design (Heckerman, 1998; Wang & Han, 2016; Jung, 2018). As highlighted by Heckerman (1998) in his tutorial on learning with BNs, these networks excel at representing and reasoning about probabilistic dependencies, including causal ones within data. The inference process in a BN also supports dynamic updating of beliefs as new evidence becomes available, making them ideal for adaptive learning environments (Wang & Han, 2016). This capability allows researchers to move beyond simple correlations and explore how specific educational practices directly influence student outcomes.

3. RESULTS AND DISCUSSION

3.1. Experimental Settings and Data

This study conducted numerical experiments using LMS data collected from 2023 to 2024 for an online Mathematics undergraduate course at University A, a public university in Malaysia. To create a focused and manageable BN model, the analysis was narrowed to a single, well-defined topic within the course. This approach enabled a detailed examination of the relationships between learning analytics variables, including student engagement and participation, and their impact on academic performance within that specific topic. The variables used to construct the BN model are outlined in Table 1. To effectively capture the discrete states relevant for BN analysis, several variables were discretized, ensuring they adhere to the structure required for CPT calculation. For example, 'COURSE_PART' and 'ATTENDANCE_RATE' were categorized into 'Low,' and 'High' to reflect varying levels of student participation. The variable 'GENERAL_PRO', 'VIDEO', and 'LECTURER' were categorized as 'Yes' or 'No' to indicate prior topic experience, while 'MODULE', 'GAMIFICATION' and 'ASSESSMENT' were classified as 'Complete' or 'Not Complete' based on completion status. Finally, the variable 'EXAM_GRADE' was discretized into 'Poor', 'Average', 'Good', and 'Excellent' categories, providing a granular assessment of performance. The experimental methodology involved a 70/30 train-test split (holdout method) of the 2023-2024 dataset. BN model is constructed using GeNIe Modeler (BayesFusion, 2025), which was selected for its user-friendly design, flexible data generation tools, and academic accessibility.

3.2. Application of BN for LMS Data

Due to data limitations and the necessity of incorporating pedagogical expertise, the network structure was determined through expert elicitation. Expert in Mathematics education were engaged to identify and establish the connections between key variables, including student engagement, prior knowledge, and academic performance. After defining the network structure, the parameters were estimated using the Expectation-Maximization (EM) algorithm applied to the training dataset. The EM algorithm iteratively refined the CPTs to reflect the patterns observed in the data. The BN modeled in GeNIe Modeler visually represents the BN structure (Figure 2) and the learned probabilities (Figure 3). BN shows the complex interplay of factors influencing students' exam grades through a network of ten variables (Figure 2). The network models a causal path-way, beginning with input nodes to the final performance outcome. The input nodes represent key factors affecting student learning, such as attendance rate, course participation, and general proficiency or prior knowledge of the topic. These inputs influence intermediate nodes such as online lecture, course module, and supplementary video, which signify the various modes of learning delivery. Subsequently, these affecting the course evaluation activities such as computer laboratory work, assessment, and gamification quizzes. Ultimately, these outcome influencing nodes collectively determine the final examination grade, serving as the culminating indicator of academic performance.

Table 1. Variables used in the BN model for academic performance prediction using LMS data

Variable	Description	Possible values
GENERAL_PRO	General proficiency whether a student has prior experience of the topic	Yes, No
COURSE_PART	Student's participation in activities in the LMS	Low, High
ATTENDANCE_RATE	The percentage of scheduled classes or sessions a student attends	Low, High
MODULE	Completion of topic module	Complete, Not complete
VIDEO	Completion of watching supplementary video	Yes, No
LECTURE	Attended the online lecture	Yes, No
GAMIFICATION	Participation in gamified quizzes	Complete, Not complete
ASSESSMENT	Completion of the assessment	Complete, Not complete
LAB_WORK	Participation in lab exercises	Low, Moderate, High
EXAM_GRADE	The final exam score categorized into different performance levels	Poor, Average, Good, Excellent

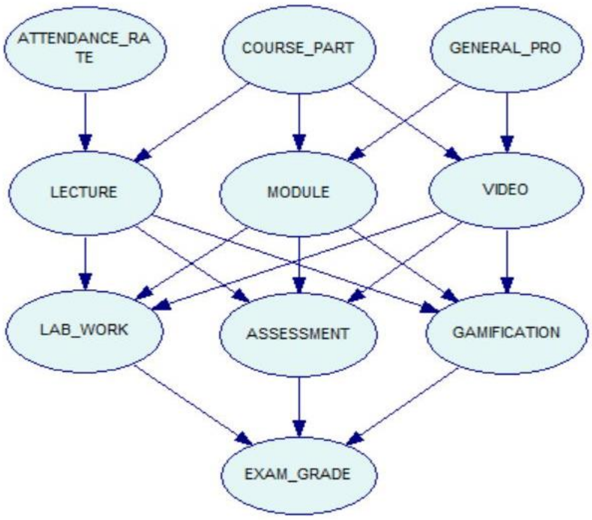


Figure 2. BN structure for academic performance

The parameters of the BN were learned through the Expectation-Maximization (EM) algorithm, an iterative process that refines the CPTs based on the observed data. One major benefit of using the EM algorithm is its ability to handle incomplete or missing data, ensuring that the BN accurately represents the underlying probabilistic relationships. This leads to a more robust and reliable model that better captures the complexities of student behavior and learning processes. The resulting BN model is visualized in GeNIe Modeler (Figure 3).

A key finding is the direct causal link between high 'ATTENDANCE_RATE' (88% 'Yes') and moderate 'COURSE_PART' participation (50% 'Yes') leading to strong 'LECTURE' engagement (85% 'Yes'), highlighting that consistent attendance with active course involvement fosters greater engagement during lectures. While 'COURSE_PART' is evenly split (50% 'Yes') and 'GENERAL_PRO' demonstrates a modest positive influence (38% 'Yes'), both contribute to moderate engagement with completion of 'MODULE' (50% 'Yes') and 'VIDEO' (55% 'Yes'). These learning activities subsequently affect 'ASSESSMENT' performance, which is skewed towards lower scores (61% 'Low'), and 'GAMIFICATION' engagement, also predominantly low (61% 'Low'). In contrast, 'LAB_WORK' exhibits strong student involvement, with 62% showing high engagement. Despite challenges reflected in assessment outcomes and gamification participation, a notable portion of students achieve 'Good' (37%) and 'Excellent' (25%) in 'EXAM_GRADE'. This pattern suggests that while some learning activities may see limited engagement or effectiveness, factors such as consistent attendance and hands-on lab work play a crucial role in driving academic success. The interplay among these variables highlights the multifaceted nature of learning, where active, practical involvement can compensate for weaker areas, underscoring the need to balance different instructional strategies within LMS environments.

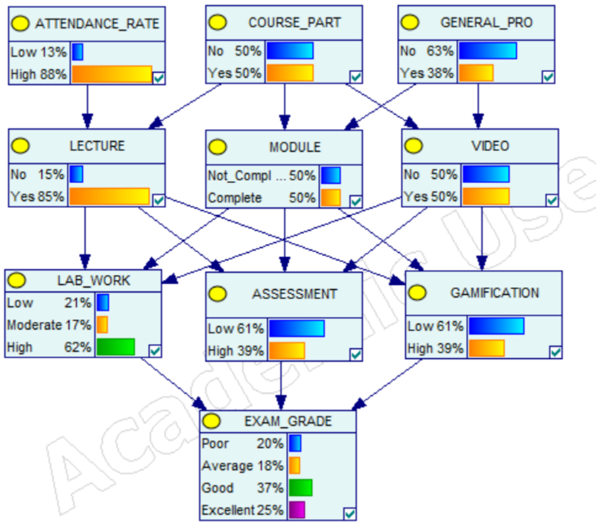


Figure 3. BN with learned parameters

3.3. Experiment 1: Prediction of Academic Underachievement

This experiment aims to identify factors contributing to poor academic performance by simulating a scenario in which students consistently receive ‘Poor’ exam grades and exhibit unsatisfactory performance across all learning delivery methods. Evidence is set in the target node ‘EXAM_GRADE’ to 100% ‘Poor’ and in the intermediate nodes ‘LAB_WORK’, ‘ASSESSMENT’ and ‘GAMIFICATION’ to 100% ‘Low’ establishing a condition where students are known with certainty to have failed and struggled with learning activities. By applying Bayesian inference using Eq. (1) to compute the joint distribution of all variables, the model analyses the resulting probability distribution (illustrated in Figure 4).

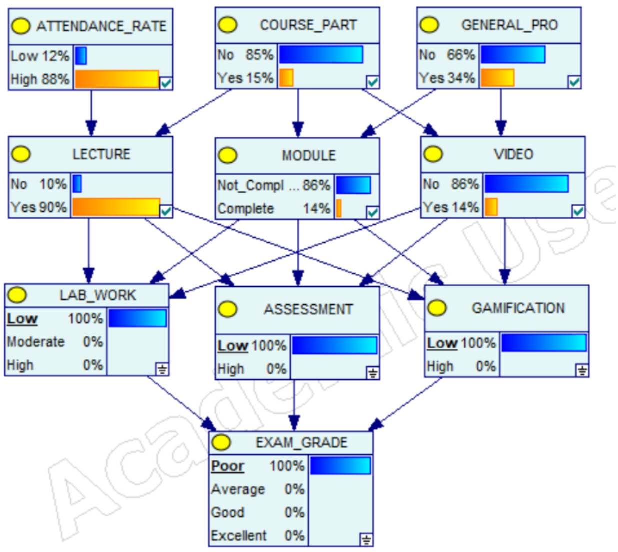


Figure 4. BN used in Experiment 1 to predict factors contributing to poor academic performance

The BN infers that ‘COURSE_PART’ node indicates a high rate of non-participation (82% ‘No’), highlighting a strong association between lack of participation and poor performance. Similarly, the ‘MODULE’ and ‘VIDEO’ nodes show high rates of non-completion or non-utilization (83% each), reinforcing the association between disengagement and underachievement. Notably, the ‘GENERAL_PRO’ node, with a 66% ‘No’ rate, suggests that students without prior knowledge are more prone to poor performance. Crucially, despite the evidence showing high attendance (88% 'High') and lecture engagement (88% 'Yes'), students still achieved poor grades. This unexpected finding highlights that mere physical presence or passive consumption of lectures is insufficient to drive success. This result strongly confirms the need for instructional strategies that move beyond traditional attendance tracking to focus on active, measurable engagement (e.g., participation, completion rates) to improve learning outcomes.

3.4. Experiment 2: Projecting Future Student Outcomes

Experiment 2 explores how altering key contributing factors can influence future student performance. Unlike Experiment 1, which focused on diagnosing the causes of poor performance, this experiment projects potential outcome under hypothetical favorable conditions. Specifically, it examines how changes in key learning factors such as student engagement and learning delivery affects academic results. The variable 'COURSE_PART' is set to 100% 'Yes' indicating full student participation, and 'GENERAL_PRO' is set to 100% 'Yes' reflecting high prior knowledge. Similarly, the variable 'MODULE' is set to 100% 'Complete' and 'VIDEO' to 100% 'Yes' representing complete module engagement and full utilization of video resources. The updated network results using Eq. (1) is presented in Figure 5, where the joint probabilities are effectively propagated through the network by incorporating the introduced evidence.

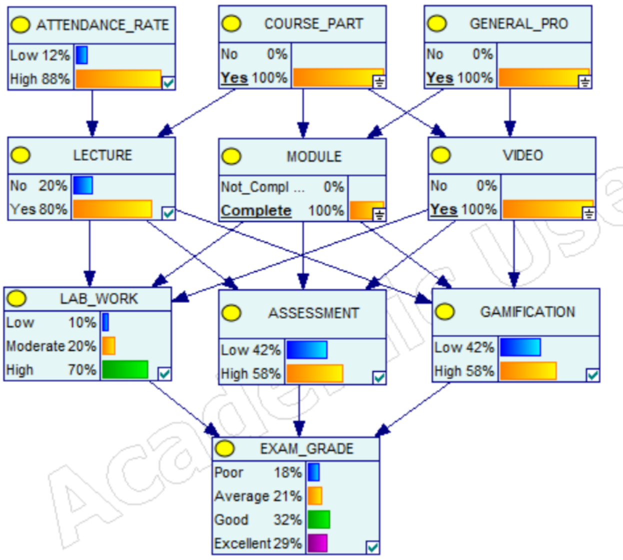


Figure 5. BN used in Experiment 2 to simulate the impact of improvements in key learning factors on academic performance

The simulation reveals a potential increase in 'LAB_WORK' engagement from 70% to 90% 'High', a substantial rise in 'GAMIFICATION' engagement from 58% to 85% 'High', and a reduction in low 'ASSESSMENT' scores from 42% to 10%. Most importantly, these improvements significantly shift the 'EXAM_GRADE' distribution, increasing the percentage of 'Excellent' grades from 29% to 60%, while simultaneously reducing 'Poor' grades from 18% to 5%. These results demonstrate the substantial positive impact that enhanced student engagement and preparation can have on academic performance. The findings confirm the predictive potential of the BN for evaluating improved learning strategies, particularly those focusing on active participation, ensuring high prior knowledge readiness, and promoting complete utilization of digital resources.

3.5. Performance prediction

To evaluate the effectiveness of the BN in capturing the complex relationships influencing student exam outcomes, a comprehensive model evaluation analysis was performed. The performance metrics for the prediction of 'EXAM_GRADE' are summarized in Table 2. Standard classification metrics (precision, recall, F1-score, and accuracy) were used to evaluate the model's performance, with the lower and upper bounds of the 95% confidence interval reported. These classification metrics were generated using k-fold cross-validation technique (k=4) to provide a more robust estimate of model performance compared to a single train-test split. The precision value indicates that 67% of predicted positive cases were correct, though the wide confidence interval suggests substantial variability across folds. This suggests the model has some ability to identify positive cases, but also produces a number of false positives. The recall score was 0.5833 [0.2248, 0.9419], meaning the model successfully identified approximately 58% of actual positive cases, with considerable uncertainty. The F1-score, which combines precision and recall, was 0.33, reflecting the imbalance between these two measures and indicating that the model struggles to balance them. The model achieved an accuracy of 0.50, demonstrating consistent but limited predictive capability across all folds. Given the multi-class nature of the target variable, 'EXAM_GRADE' and class imbalance in the underlying dataset, this 50% accuracy suggests the model is better than random guessing but faces significant limitations in real-world generalization.

Table 2. Performance metric for prediction 'EXAM_GRADE'

Metric	Value
Precision	0.67 [0.3081, 1.0252]
Recall	0.58 [0.2248, 0.9419]
F1-Score	0.33 [0.3333, 0.3333]
Accuracy	0.50 [0.5000, 0.5000]
Log-likelihood	-31.89
Akaike Information Criterion (AIC)	77.79
Bayesian Information Criterion (BIC)	79.17

In addition to the classification metrics, probabilistic performance measures including the log-likelihood, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) were also evaluated. The log-likelihood for the model was -31.89, which quantifies the probability of observing the specific training data given the structure and estimated parameters of the BN. Meanwhile, both AIC and BIC were used to evaluate the trade-off between goodness-of-fit (how well the model explains the data) and the model's complexity (the number of free parameters). Lower values for AIC and BIC generally indicate a superior model. The calculated AIC (77.79) and BIC (79.17) values suggest that the current structure may be overly complex relative to how well it fits the available data. This indicates that the BN has room for structural refinement or simplification to achieve a more parsimonious representation, which should improve generalization. This moderate performance is likely attributed to data limitations, including a potentially small dataset lacking sufficient variability, the presence of missing or noisy data, and the possible exclusion of crucial variables. Furthermore, overfitting might be a contributing factor, as evidenced by the model's better performance on higher grade classifications, suggesting it may have memorized training data patterns that don't generalize well. To improve the model's performance, future work should focus on increasing the dataset size, conducting feature engineering to create more informative inputs, and adding more relevant features to the model.

4. CONCLUSION

This study successfully demonstrated the application of BNs to analyze academic performance using LMS data. The BN model effectively captured the complex relationships between student engagement, learning delivery methods, and academic outcomes, validating the use of causal probabilistic modeling in EDM. The numerical experiments yielded critical insights into the factors driving success and failure. Specifically, the model revealed that passive engagement (high attendance alone) is insufficient for success, and the absence of prior general proficiency was strongly associated with poor outcomes. Conversely, simulation experiments projected that targeted interventions focused on boosting active participation and enhancing key delivery methods (e.g., lab work, assessments, and gamification) could lead to substantial improvements in final exam results. Despite these interpretive strengths, the performance evaluation of the BN model yielded a moderate overall accuracy, which highlights the current limitations imposed by data constraints and possible overfitting. Future research should prioritize expanding the dataset to incorporate a broader range of variables, such as socio-demographic factors and motivational aspects to enhance model generalizability. Additionally, employing advanced BN learning algorithms (including dynamic and hybrid models) is necessary to improve predictive accuracy and structural fit. Ultimately, integrating these BN models with real-time LA systems could facilitate personalized interventions and adaptive learning pathways, thereby contributing to improved educational practices and student outcomes.

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CONFLICT OF INTEREST
The authors declare no conflicts of interest.

AUTHOR CONTRIBUTION
Nurulhuda Ramli: Conceptualization, Data collection, Analysis and Writing original draft. Mohd Tahir Ismail: Reviewing and Supervision. Huda Zaki Naji: Visualization

DATA AVAILABILITY
The datasets generated during and/or analyzed during the current study are not publicly available due to ethical restrictions related to participant consent and privacy but are available from the corresponding author on reasonable request.

DECLARATION OF GENERATIVE AI
During the preparation of this work, the author(s) used Gemini to assist with brainstorming and grammatical checks. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

ETHICS
Not applicable.

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