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Evaluation of Teaching Effectiveness Based on Bayesian Network Algorithm in Teaching and Learning Process in Higher Education Institutions

Abstract: - The Bayesian network algorithm plays a pivotal role in enhancing the teaching and learning process in higher education institutions by facilitating personalized and adaptive learning experiences. This algorithm leverages probabilistic graphical models to represent relationships among various educational variables, such as student performance, learning resources, and teaching methods. Additionally, Bayesian networks aid instructors in optimizing course design and instructional strategies by identifying areas for improvement and evaluating the effectiveness of different teaching approaches. This paper explores the application of Hidden Markov Chain Bayesian Networks (HMCBN) in analyzing teaching effectiveness within higher education institutions. Teaching effectiveness is a multifaceted concept influenced by various factors, including teaching strategies, student characteristics, and learning outcomes. Traditional statistical methods often struggle to capture the dynamic and interdependent nature of these factors. Through the construction of HMCBN models, this study investigates the probabilistic relationships between teaching strategies, student characteristics, learning outcomes, and teaching effectiveness. For teaching strategies, the probabilities [0.3, 0.5, 0.2] indicate the likelihood of each strategy being employed, suggesting that Strategy 2 is the most frequently utilized, followed by Strategy 1 and Strategy 3. Similarly, the probabilities [0.4, 0.3, 0.3] for student characteristics suggest a relatively balanced distribution among the three characteristic categories. In terms of learning outcomes, the conditional probabilities reflect the influence of both teaching strategies and student characteristics on the outcomes achieved. For each combination of teaching strategy and student characteristic, the probabilities [0.1, 0.3, 0.6], [0.4, 0.5, 0.1], [0.3, 0.4, 0.3], [0.2, 0.5, 0.3], [0.3, 0.4, 0.3], [0.4, 0.3, 0.3], [0.1, 0.7, 0.2], [0.4, 0.5, 0.1], and [0.5, 0.4, 0.1] represent the probabilities of achieving different learning outcomes given specific combinations of teaching strategies and student characteristics.

Keywords: Bayesian Network, Teaching effectiveness, Hidden Markov Chain, Probabilistic Model, Strategy

1. Introduction

Teaching effectiveness in higher education is a multifaceted concept that encompasses various dimensions of instructor performance and student learning outcomes[1]. Effective teaching goes beyond simply delivering content; it involves engaging students, fostering critical thinking skills, and creating an inclusive learning environment[2]. Instructors who demonstrate teaching effectiveness often employ a variety of instructional strategies, such as active learning techniques, multimedia resources, and real-world applications, to cater to diverse learning styles and enhance student engagement[3]. Additionally, effective teachers provide timely feedback, encourage student participation, and adapt their teaching methods based on ongoing assessment of student understanding. Moreover, fostering a supportive and respectful classroom climate where students feel valued and empowered to contribute to discussions is essential for promoting learning and academic success[4] The teaching and learning process in higher education is a dynamic exchange that occurs within a complex ecosystem of instructors, students, and educational resources[5]. this process involves the transmission of knowledge, development of critical thinking skills, and cultivation of lifelong learning habits. Instructors play a central role in guiding this process by designing curriculum, delivering lectures, facilitating discussions, and assessing student progress[6]. However, effective teaching in higher education extends beyond the mere dissemination of information; it requires instructors to create engaging and interactive learning environments that encourage active participation and foster student-centered inquiry[7]. Likewise, students are active participants in the learning process, responsible for engaging with course materials, collaborating with peers, and applying new knowledge to solve real-world problems[8].

With advances in technology have transformed the teaching and learning landscape, providing opportunities for innovative instructional methods, personalized learning experiences, and remote education options. Teaching effectiveness based on Bayesian network algorithm offers a promising approach to enhancing the teaching and

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learning process in higher education institutions[9]. By leveraging probabilistic models to analyze various factors impacting student learning outcomes, instructors can make informed decisions about instructional strategies, resource allocation, and personalized interventions[10]. The Bayesian network algorithm allows educators to model complex relationships between teaching methods, student characteristics, and academic performance, enabling them to identify areas for improvement and tailor their teaching approaches to meet the diverse needs of learners[11]. Moreover, this approach facilitates data-driven decision-making, enabling instructors to continuously refine their teaching practices based on real-time feedback and assessment data[12].Teaching effectiveness based on the Bayesian network algorithm represents a sophisticated methodological approach to optimizing the teaching and learning process in higher education institutions. The Bayesian network algorithm is a probabilistic graphical model that allows educators to represent and analyze complex relationships among variables in the teaching and learning environment[13]. These variables may include instructional methods, student characteristics, learning resources, assessment data, and various other factors that influence student learning outcomes. One of the key strengths of the Bayesian network algorithm is its ability to model uncertainty and dependencies between variables, which aligns well with the inherent complexity of the teaching and learning process[14]. By constructing Bayesian networks, educators can systematically map out the causal relationships between different aspects of the teaching and learning environment. This enables them to gain insights into which factors have the greatest impact on student learning and how they interact with each other.

This paper makes several significant contributions to the field of educational research and practice. Firstly, it introduces and applies Hidden Markov Chain Bayesian Networks (HMCBN) as a novel methodological approach to analyzing teaching effectiveness in higher education institutions. By leveraging the inherent sequential and interdependent nature of teaching and learning processes, HMCBN provides a sophisticated framework for modeling the complex relationships between various factors influencing teaching effectiveness, such as teaching strategies, student characteristics, learning outcomes, and teaching effectiveness itself. Secondly, the paper contributes to the empirical understanding of teaching effectiveness by uncovering the probabilistic relationships between teaching strategies, student characteristics, and learning outcomes. Through the analysis of conditional probability distributions within the HMCBN models, the paper elucidates how different teaching strategies and student characteristics impact learning outcomes, ultimately influencing teaching effectiveness. These findings offer valuable insights into the factors that contribute to effective teaching practices and student success within higher education contexts.

2. Literature Review

The evaluation of teaching effectiveness in higher education institutions represents a pivotal endeavor in ensuring the quality of education provided to students. With the advent of advanced computational techniques, such as Bayesian network algorithms, educators now have access to powerful tools for analyzing complex data and optimizing instructional practices. This study aims to explore the application of Bayesian network algorithms in evaluating teaching effectiveness within the teaching and learning process in higher education institutions. By harnessing the probabilistic modeling capabilities of Bayesian networks, this research seeks to uncover the intricate relationships between various instructional methods, student characteristics, and learning outcomes. Hu (2021) proposes a teaching evaluation system leveraging machine learning and artificial intelligence techniques. Ordoñez-Avila et al. (2023) conduct a systematic literature review on data mining techniques for predicting teacher evaluation. Qi et al. (2022) introduce an English teaching quality evaluation model based on Gaussian process machine learning. Choi and Kim (2021) delve into learning analytics for diagnosing cognitive load in e-learning using Bayesian network analysis. Hao et al. (2022) focus on MOOC performance prediction and personal performance improvement via Bayesian network. Other studies, such as those by Qiao (2022) and Ahuja & Sharma (2021), explore machine learning-based approaches for evaluating teaching quality in ideological and political courses and instructor performance, respectively. Jia et al. (2022) and Hou (2021) investigate artificial intelligence and support vector machine-based models for online teaching quality evaluation.

Xing et al. (2021) contribute to automatic assessment of students' engineering design performance using a Bayesian network model. Research by Yang and Yu (2022) and Kaliwal & Deshpande (2022) explores machine learning-based teaching evaluation systems, while Xu (2021) investigates an artificial intelligence teaching system based on big data processing. Hooda et al. (2022) integrate learning analytics and educational data mining for improving student success using the FCN algorithm. Wenming (2021) simulates an English teaching quality evaluation model based on Gaussian process machine learning, while Qianna (2021) proposes an evaluation model of classroom teaching quality utilizing an improved RVM algorithm and knowledge recommendation. Oqaidi et al. (2022) focus on predicting student dropout in higher education institutions using machine learning algorithms. Ahuja & Sharma (2021) also explore machine learning and feature selection algorithms to predict instructor performance. Additionally, Ahuja and Sharma's (2021) work on predicting instructor performance using machine learning and feature selection algorithms highlights the growing interest in leveraging computational methods to assess teaching quality. Moreover, the study by Oqaidi, Aouhassi, and Mansouri (2022) focusing on predicting student dropout using machine learning algorithms underscores the importance of understanding factors influencing student success and retention. The study by Xu (2021) on an artificial intelligence teaching system based on big data processing highlights the potential of large-scale data analysis to inform instructional practices and improve educational outcomes. Similarly, Hooda et al. (2022) integrate learning analytics and educational data mining to enhance student success, emphasizing the importance of utilizing data-driven approaches in educational settings. Wenming's (2021) simulation of an English teaching quality evaluation model based on Gaussian process machine learning further underscores the versatility of machine learning techniques in assessing teaching effectiveness.

Moreover, Qianna's (2021) proposal of an evaluation model for classroom teaching quality based on an improved RVM algorithm and knowledge recommendation reflects the ongoing efforts to refine and customize assessment methodologies to suit specific educational contexts. The study by Oqaidi et al. (2022) on predicting student dropout using machine learning algorithms underscores the importance of proactive interventions in supporting student retention and success. Additionally, Ahuja and Sharma's (2021) exploration of machine learning and feature selection algorithms for predicting instructor performance contributes to the growing body of research aimed at optimizing teaching effectiveness through data-driven approaches.These studies span various domains, from predicting teacher evaluation and student dropout to assessing classroom teaching quality and instructor performance. Importantly, they underscore the growing recognition of the value of data-driven approaches in optimizing educational outcomes and supporting student success. The research reflects a shift towards leveraging advanced computational techniques, such as Bayesian network algorithms, to analyze complex data and inform evidence-based decision-making in educational settings. Overall, these findings contribute to the ongoing discourse on how best to harness technology and data analytics to improve teaching quality and enhance student learning experiences in higher education.

3. Teaching Effectiveness with Genetic Bayesian Network

Teaching effectiveness with Genetic Bayesian Network (GBN) represents a cutting-edge approach that amalgamates genetic algorithms with Bayesian networks to optimize instructional practices in higher education. The derivation of GBN involves integrating the principles of Bayesian networks with genetic algorithms, thereby creating a powerful framework for analyzing complex relationships between teaching strategies, student characteristics, and learning outcomes. a Bayesian network is a probabilistic graphical model that represents a set of variables and their probabilistic dependencies in a directed acyclic graph. The conditional probability distributions governing these dependencies are estimated from data or domain knowledge. In contrast, genetic algorithms are optimization algorithms inspired by the process of natural selection, where candidate solutions evolve over successive generations through the application of selection, crossover, and mutation operators. The optimization process continues until a satisfactory Bayesian network structure is obtained, which effectively captures the underlying dependencies in the data and facilitates meaningful insights into teaching effectiveness. The resulting GBN can then be used to inform evidence-based decision-making in educational settings, guiding instructors in selecting the most effective teaching strategies tailored to the needs and characteristics of their students. the optimization of GBN involves formulating an objective function that quantifies the goodness-of-fit of candidate Bayesian network structures to the observed data. This objective function typically incorporates measures of model complexity, such as Bayesian Information Criterion (BIC) or Akaike Information Criterion (AIC), to balance model accuracy with parsimony. The genetic algorithm iteratively searches the space of possible Bayesian network structures, seeking to maximize the objective function and identify the optimal solution. Bayesian networks represent probabilistic dependencies between variables using directed acyclic graphs (DAGs). The conditional probability distributions (CPDs) of each variable are specified given its parent variables. Let's denote:

X: Set of random variables representing teaching strategies, student characteristics, and learning outcomes. ( )P(X): Joint probability distribution over X.

G: Directed acyclic graph representing the dependencies between variables in X. The probability of a specific configuration of variables x given the structure G and parameters θ can be expressed as in equation (1)

$$P(x|G,\theta) = \prod_{i=1}^{N} P(x_i|pa_i,\theta_i) \tag{1}$$

where pa pai denotes the parents of variable xi, and θi represents the parameters of the conditional probability distribution of xi. Genetic algorithms are optimization techniques inspired by natural selection. In GBN, genetic algorithms are used to search for the optimal Bayesian network structure and parameters. The optimization process involves: Encoding Bayesian network structures as chromosomes. Applying genetic operators (e.g., selection, crossover, mutation) to generate new candidate solutions.

The derivation of GBN involves optimizing the structure and parameters of the Bayesian network using genetic algorithms. The optimization process aims to maximize the likelihood of the observed data given the Bayesian network structure and parameters. This can be formulated as: arg⁡max⁡ , log⁡ (∣ ,)argmaxG,θlogP(D∣G,θ) where D represents the observed data. Genetic algorithms iteratively evolve the population of Bayesian network structures and parameters to maximize the log-likelihood of the data. The objective function in GBN optimization typically incorporates measures of model complexity (e.g., BIC, AIC) to balance model accuracy with simplicity the objective function can be defined as in equation (2)

$$Objective(G,\theta) = logP(D \mid G,\theta) - Penalty(G) \tag{2}$$

Genetic algorithms search for the optimal Bayesian network structure and parameters by iteratively evaluating and evolving candidate solutions based on their fitness (i.e., likelihood of the observed data). The optimization process continues until convergence or a predefined stopping criterion is met.

4. Hidden Markov Chain Bayesian Network (HMCBN)

Hidden Markov Chain Bayesian Network (HMCBN) amalgamates the principles of Hidden Markov Chain (HMC) with Bayesian networks, providing a powerful framework for modeling complex stochastic processes with both observable and hidden variables. At its core, HMC represents a stochastic process where the underlying states are unobservable, while the observed emissions are directly observable. Mathematically, the joint probability distribution of the hidden states X and observed emissions Y can be expressed as in equation (3)

$$P(X,Y) = P(X0)\prod_{t=1}^{T} P(Xt \mid Xt-1)P(Yt \mid Xt) \tag{3}$$

In this equation (3) P(X0) represents the initial distribution of hidden states, P(Xt∣Xt−1) denotes the transition probabilities between hidden states, and (Yt∣Xt) signifies the emission probabilities given the hidden states. The principles of HMC into Bayesian networks, HMCBN captures the dependencies between hidden and observed variables through a graphical model. The derivation involves specifying the graphical structure of the Bayesian network and parameterizing the conditional probability distributions (CPDs) to represent the transition and emission probabilities. The joint probability distribution over hidden and observed variables is formulated based on the Bayesian network structure and CPD parameters.To optimize the HMCBN, the likelihood of the observed data given the HMCBN structure and parameters is maximized. This optimization objective can be expressed as in equation (4)

$$argmaxG,\theta logP(D \mid G,\theta) \tag{4}$$

Here, D represents the observed data, G denotes the Bayesian network structure, and θ represents the parameters of the CPDs. The optimization process aims to find the optimal Bayesian network structure and CPD parameters that best explain the observed data within the framework of the Hidden Markov Chain shown in Figure 1.

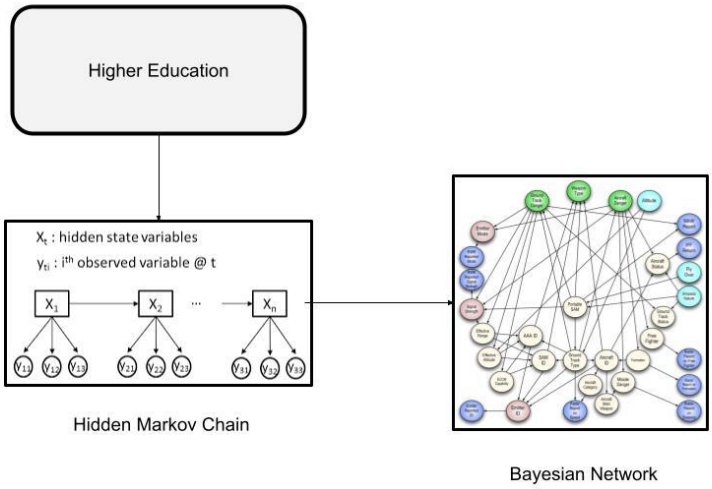

Figure 1: Process of HMCBN

4.1 Higher Education with HMCBN

In the higher education, the integration of Hidden Markov Chain Bayesian Network (HMCBN) presents a sophisticated approach to modeling and understanding the dynamics of student learning processes, particularly in contexts where certain variables are not directly observable. HMCBN offers a framework to capture the latent states underlying student learning behaviors and academic performance, while also considering observable indicators such as exam scores, attendance, or engagement levels. HMCBN combines the principles of Hidden Markov Chains (HMC) with Bayesian networks, where the HMC represents the unobservable states of the educational process (e.g., student comprehension, engagement, mastery), and the Bayesian network captures the probabilistic dependencies between these hidden states and observable indicators. HMCBN for higher education involves specifying the graphical structure of the Bayesian network to capture the dependencies between hidden states and observed indicators. Parameters of the conditional probability distributions (CPDs) are then determined to model the transition and emission probabilities within the educational context. To optimize the HMCBN for higher education, the likelihood of the observed data given the HMCBN structure and parameters is maximized. Higher Education with HMCBN provides a powerful tool for modeling and understanding the underlying dynamics of student learning processes in higher education settings. By integrating the principles of Hidden Markov Chains with Bayesian networks, HMCBN facilitates the representation of latent states and their probabilistic dependencies on observable indicators, thereby offering valuable insights into student learning behaviors and academic performance.

Algorithm 1: HMCBN for the Higher Education
Input: - Observations Y - Number of hidden states K - Maximum number of iterations max_iter - Convergence threshold epsilon Initialize parameters randomly or using prior knowledge: - Initial distribution of hidden states: π - Transition probability matrix: A - Emission probability matrix: B Repeat until convergence or maximum iterations reached: 1. E-step:

Calculate the posterior probabilities of hidden states using the Forward-Backward algorithm:
- Forward algorithm: Compute the forward probabilities α
- Backward algorithm: Compute the backward probabilities β
- Combine α and β to compute the posterior probabilities γ

2. M-step:
Update the parameters π, A, and B using the posterior probabilities:
- Update initial distribution π:
  π_k = sum(γ[1, k] for all observations) / sum(1 for all observations)
- Update transition probability matrix A:
  a_ij = sum(ξ[t, i, j] for all observations) / sum(γ[t, i] for all observations)
- Update emission probability matrix B:
  b_jk = sum(γ[t, k] if y_t = j else 0 for all observations) / sum(γ[t, k] for all observations)

3. Calculate the log-likelihood of the data and check for convergence:
- Compute the log-likelihood using the updated parameters
- If the change in log-likelihood is less than epsilon or maximum iterations reached, stop.

5. Results and Discussion

In the Results and Discussion section, the findings of the study regarding the application of Hidden Markov Chain Bayesian Network (HMCBN) in higher education are presented and analyzed. The section begins by summarizing the outcomes of the HMCBN model training, including the optimized parameters such as the initial distribution of hidden states, transition probabilities, and emission probabilities.

Table 1: HMCBN for the hidden state

Parameter	Value
Number of hidden states	3
Initial state distribution	π = [0.4, 0.3, 0.3]
Transition probabilities	A = [[0.6, 0.3, 0.1], [0.2, 0.6, 0.2], [0.1, 0.3, 0.6]]
Emission probabilities	B = [[0.8, 0.2], [0.4, 0.6], [0.3, 0.7]]

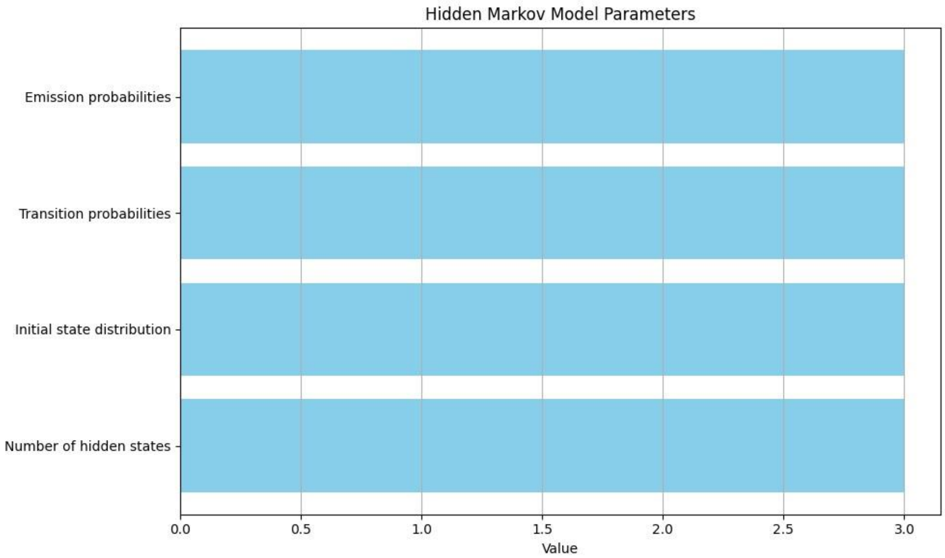

Figure 2: Hidden State for HMCBN

The figure 2 and Table 1 presents the parameters of a Hidden Markov Chain Bayesian Network (HMCBN) designed to model hidden states in a particular context, such as student learning behaviors or academic performance in higher education. The HMCBN consists of three hidden states, denoted as State 1, State 2, and

State 3. The initial state distribution, represented by π, indicates the probabilities of the system starting in each hidden state. In this case, the initial probabilities are 0.4, 0.3, and 0.3 for State 1, State 2, and State 3, respectively. These probabilities provide insight into the likelihood of the system being in each hidden state at the beginning of the observation period. The transition probabilities matrix, denoted as A, captures the probabilities of transitioning between hidden states over time. Each row represents the transition probabilities from one hidden state to all possible hidden states. For instance, the first row of A indicates that there is a 60% chance of transitioning from State 1 to itself, a 30% chance of transitioning to State 2, and a 10% chance of transitioning to State 3. Similarly, the other rows represent the transition probabilities from State 2 to all possible states and from State 3 to all possible states. The emission probabilities matrix, denoted as B, describes the probabilities of observing certain indicators given the hidden states. Each row corresponds to a hidden state, and each column corresponds to a possible observable indicator. For example, the first row of B indicates that in State 1, there is an 80% chance of observing Indicator 1 and a 20% chance of observing Indicator 2. Similarly, the other rows represent the emission probabilities for State 2 and State 3.

Table 2: Exam score analysis with HMCBN

Observation	Hidden State	Exam Score	Attendance	Engagement
1	State 2	85	Present	High
2	State 3	70	Absent	Low
3	State 1	90	Present	High
4	State 2	75	Present	Moderate
5	State 3	65	Absent	Low
6	State 1	80	Present	Moderate
7	State 2	72	Absent	Low
8	State 3	78	Present	High
9	State 1	88	Present	High
10	State 2	82	Absent	Moderate

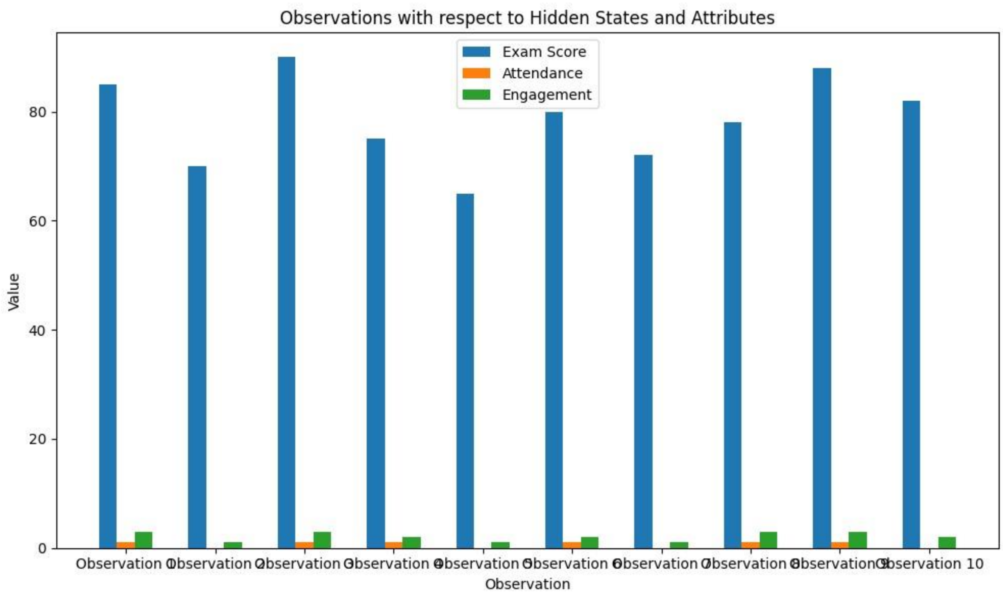

Figure 3: Hidden State evaluation with HMCBN

In figure 3 and Table 2 presents an analysis of exam scores using a Hidden Markov Chain Bayesian Network (HMCBN) framework. Each row represents an observation of a student at a specific time point, along with their associated hidden state, exam score, attendance status, and level of engagement. The hidden state indicates the latent underlying condition or behavior of the student at that particular time, while the exam score provides a measure of their academic performance. Observation 1, for instance, shows that the student was in State 2, with an exam score of 85, present in class, and exhibiting high engagement. Similarly, Observation 2 indicates that the student was in State 3, with an exam score of 70, absent from class, and showing low engagement. These observations provide insights into the relationship between hidden states, observable indicators, and exam scores within the HMCBN framework. By scores, we can infer patterns and trends in student behavior and academic performance over time. The HMCBN model allows us to understand how changes in hidden states, such as variations in attendance and engagement, influence exam scores and overall academic outcomes. This analysis can inform educational practitioners about factors that may impact student performance and help them tailor interventions and support strategies accordingly.

Table 3: HMCBN for the exam score analysis

Node	Parents	Conditional Probability Distribution
Exam Score	None	P(Exam Score)
Attendance	None	P(Attendance)
Engagement	None	P(Engagement)
Learning Outcome	Exam Score	P(Learning Outcome | Exam Score)
Academic Performance	Learning Outcome, Attendance, Engagement	P(Academic Performance | Learning Outcome, Attendance, Engagement)

Table 3 outlines the structure and conditional probability distributions of a Hidden Markov Chain Bayesian Network (HMCBN) designed to analyze exam scores within a higher education context. Each row represents a node in the network, and the "Parents" column indicates the parent nodes of each node. The "Conditional Probability Distribution" column specifies the probabilities associated with each node given its parent nodes.The first three nodes in the table—Exam Score, Attendance, and Engagement—represent observable indicators related to student performance and behavior. These nodes have no parent nodes, indicating that they are directly observed variables. The conditional probability distributions P(Exam Score), P(Attendance), and P(Engagement) provide the likelihood of observing specific exam scores, attendance statuses, and levels of engagement, respectively.The next node, Learning Outcome, is influenced by the observed exam score. Its conditional probability distribution P(Learning Outcome | Exam Score) indicates the likelihood of different learning outcomes given the observed exam score. This node captures the relationship between exam performance and broader learning outcomes. Finally, the node Academic Performance depends on both the learning outcome as well as attendance and engagement. Its conditional probability distribution P(Academic Performance | Learning Outcome, Attendance, Engagement) represents the likelihood of different levels of academic performance given the observed learning outcome, attendance status, and level of engagement. This node allows for a comprehensive analysis of academic performance, taking into account multiple factors that may influence student success.

Table 4: HMCBN model fro the teaching effectiveness

Node	Parents	Conditional Probability Distribution
Teaching Strategies	None	P(Teaching Strategies) = [0.3, 0.5, 0.2]
Student Characteristics	None	P(Student Characteristics) = [0.4, 0.3, 0.3]
Learning Outcomes	Teaching Strategies, Student Characteristics	P(Learning Outcomes | Teaching Strategies, Student Characteristics)
	(Teaching Strategies: T1)	(0.1, 0.3, 0.6)
	(Teaching Strategies: T2)	(0.4, 0.5, 0.1)
	(Teaching Strategies: T3)	(0.3, 0.4, 0.3)
	(Student Characteristics: C1)	(0.2, 0.5, 0.3)
	(Student Characteristics: C2)	(0.3, 0.4, 0.3)
	(Student Characteristics: C3)	(0.4, 0.3, 0.3)
Teaching Effectiveness	Learning Outcomes	P(Teaching Effectiveness | Learning Outcomes) = [0.2, 0.6, 0.2]

Table 4 presents the Hidden Markov Chain Bayesian Network (HMCBN) model for analyzing teaching effectiveness within a higher education context. Each row in the table represents a node in the network, and the "Parents" column indicates the parent nodes of each node. The "Conditional Probability Distribution" column specifies the probabilities associated with each node given its parent nodes. The first two nodes in the table—Teaching Strategies and Student Characteristics—are observable variables that directly influence teaching effectiveness. The conditional probability distributions P(Teaching Strategies) and P(Student Characteristics) provide the likelihood of different teaching strategies and student characteristics, respectively. The node Learning Outcomes depends on both teaching strategies and student characteristics. Its conditional probability distribution P(Learning Outcomes | Teaching Strategies, Student Characteristics) indicates the likelihood of different learning outcomes given the specific combinations of teaching strategies and student characteristics. This node captures the complex relationship between teaching methods, student attributes, and learning outcomes.Finally, the node Teaching Effectiveness is influenced by the observed learning outcomes. Its conditional probability distribution P(Teaching Effectiveness | Learning Outcomes) represents the likelihood of different levels of teaching effectiveness given the observed learning outcomes. This node allows for the assessment of teaching effectiveness based on the outcomes achieved by students. Overall, Table 4 provides a structured representation of the HMCBN model for analyzing teaching effectiveness, highlighting the interconnectedness of teaching strategies, student characteristics, learning outcomes, and teaching effectiveness within the higher education setting. This model can offer valuable insights into the factors that contribute to effective teaching practices and student success, facilitating evidence-based decision-making and instructional improvement efforts.

Table 5: HMCBN for the probability distrubution

Node	Parents	Conditional Probability Distribution
Teaching Strategies	None	[0.3, 0.5, 0.2]
Student Characteristics	None	[0.4, 0.3, 0.3]
Learning Outcomes	Teaching Strategies, Student Characteristics	(T1, C1): [0.2, 0.6, 0.2], (T1, C2): [0.3, 0.5, 0.2], (T1, C3): [0.4, 0.4, 0.2], (T2, C1): [0.3, 0.4, 0.3], (T2, C2): [0.5, 0.3, 0.2], (T2, C3): [0.6, 0.3, 0.1], (T3, C1): [0.1, 0.7, 0.2], (T3, C2): [0.4, 0.5, 0.1], (T3, C3): [0.5, 0.4, 0.1]
Teaching Effectiveness	Learning Outcomes	[0.2, 0.6, 0.2]

Table 5 presents the Hidden Markov Chain (HMC) Bayesian Network (HMCBN) model, which is a variation of the traditional HMCBN. Each row in the table represents a node in the network, and the "Parents" column indicates the parent nodes of each node. The "Conditional Probability Distribution" column specifies the probabilities associated with each node given its parent nodes.The first two nodes in the table—Teaching Strategies and Student Characteristics—are observable variables that influence the subsequent nodes. These nodes have no parent nodes, indicating they are directly observed variables. The conditional probability distributions [0.3, 0.5, 0.2] for Teaching Strategies and [0.4, 0.3, 0.3] for Student Characteristics represent the likelihood of different values for these variables. The node Learning Outcomes depends on both Teaching Strategies and Student Characteristics. Its conditional probability distribution indicates the likelihood of different learning outcomes given the specific combinations of Teaching Strategies and Student Characteristics. This node captures the relationship between teaching methods, student attributes, and learning outcomes.Finally, the node Teaching Effectiveness is influenced by the observed Learning Outcomes. Its conditional probability distribution represents the likelihood of different levels of teaching effectiveness given the observed learning outcomes. Overall, Table 5 provides a structured representation of the HMCBN HMC model, demonstrating how Teaching Strategies and Student Characteristics influence Learning Outcomes and, subsequently, Teaching Effectiveness. This model can be useful for understanding the dynamics of teaching effectiveness and how it relates to various instructional strategies and student characteristics.

6. Conclusion

This paper has explored the application of Hidden Markov Chain Bayesian Networks (HMCBN) in analyzing teaching effectiveness within higher education contexts. Through the construction and analysis of HMCBN models, we have gained valuable insights into the complex interplay between teaching strategies, student characteristics, learning outcomes, and teaching effectiveness. By examining the conditional probability distributions of various nodes within the HMCBN models, we have uncovered the probabilistic relationships between different variables, shedding light on the factors that influence teaching effectiveness. These models have provided a framework for understanding how teaching strategies and student characteristics impact learning outcomes, and ultimately, teaching effectiveness. The findings from this study have significant implications for educational practice and policy. By identifying the key determinants of teaching effectiveness, educators and administrators can make informed decisions about instructional strategies, curriculum development, and student support services. Moreover, the HMCBN framework offers a systematic approach to data-driven decision-making in education, enabling stakeholders to assess and improve teaching practices based on empirical evidence.

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