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Self-Efficacy prediction model Using Bayesian Networks

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ABSTRACT

This study introduces a Bayesian network model designed to predict teacher self-efficacy, a critical factor influencing pedagogical effectiveness. The model integrates a range of teacher characteristics, including educational background, professional experience, training, attitudes, and burnout indicators, to provide a probabilistic estimate of self-efficacy. A survey of 44 secondary school teachers in N'Djamena, Chad, was conducted to gather data for model validation. The results demonstrate the model's ability to effectively predict both individual and collective self-efficacy, highlighting the significant impact of factors such as emotional exhaustion and attitude on teachers' perceived competence. The findings suggest that this model can serve as a valuable tool for educational administrators in developing targeted interventions and support programs to enhance teacher well-being and improve classroom effectiveness. Future research should explore the integration of machine learning techniques to refine predictive accuracy and expand the model's applicability across diverse educational contexts.

Keywords: lorem Teacher Self-Efficacy, Bayesian Networks, Educational Monitoring, Teacher Burnout, Prediction Models

INTRODUCTION

Education forms the bedrock of societal advancement, necessitating robust and reliable educational systems for national progress. At the heart of such systems lies the critical role of human resources, particularly teachers, whose effectiveness directly impacts student outcomes. Consequently, meticulous monitoring of teachers' performance, termed educational monitoring, becomes indispensable [1]. The term "monitoring" encompasses two key aspects: firstly, the systematic observation and control of a process to achieve desired outcomes under optimal conditions, as seen in business or product management; and secondly, the continuous oversight of a longitudinal experience, treatment, or intervention, exemplified by medical monitoring of students. However, effectively monitoring teachers presents a complex challenge, demanding sophisticated tools and methodologies. Traditional approaches, such as databases and data warehouses with data marts, often fall short by neglecting the nuanced personal characteristics that significantly influence teachers' performance. This research addresses this gap by proposing a novel approach that leverages these personal attributes to predict teachers' sense of self-efficacy. Self-efficacy, defined as an individual's belief in their capacity to organize and execute actions required to achieve specific outcomes [2-5] plays a pivotal role in pedagogical effectiveness. Teachers with a strong sense of self-efficacy exhibit greater confidence in their ability to positively impact students, while those with low self-efficacy may perceive their influence as limited [6, 7]. Furthermore, research indicates that teachers' self-efficacy shapes their pedagogical conceptions and practices, directly affecting student learning [8]. Individuals with high self-efficacy tend to approach challenges with resilience, viewing them as opportunities for growth rather than threats [6]. Existing literature demonstrates the relevance of predicting self-efficacy [8, 9]. For instance, [9] developed multiple regression models to predict self-efficacy subscales and general self-efficacy among teachers working with students with autism spectrum disorder. Other studies have explored mathematical models based on multiple intelligences for self-efficacy prediction [10], particularly in uncertain planning scenarios within artificial intelligence (AI) research [11]. Additionally, researchers have investigated the relationship between teachers' self-efficacy, classroom management practices, and student behavior, employing Bayesian networks to model the influence of multiple intelligences on self-efficacy [10]. Building upon these foundations, this research introduces a Bayesian network-based prediction model that incorporates a

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comprehensive set of teachers' personal characteristics, including training, experience, attitude, burnout, depersonalization, accomplishment, and emotional exhaustion. By treating these characteristics as predictive variables, the model aims to generate a detailed profile of teachers based on their predicted self-efficacy [12, 13]. This profile can serve as a valuable tool for educational monitoring and intervention, enabling targeted support and professional development [14]. The remainder of this document is structured as follows: Section 2 outlines the methodology employed in this research, Section 3 presents and discusses the findings, and Section 4 concludes the paper with a summary of key contributions and future directions.

METHODOLOGY

This research employs a hybrid approach, leveraging both statistical methods and artificial intelligence (AI) techniques, specifically Bayesian networks, to predict teacher self-efficacy. Bayesian networks, a powerful tool for knowledge representation and probabilistic reasoning, offer a robust framework for handling uncertainty and modeling complex relationships between variables.

Bayesian Networks: Theoretical Foundation

Bayesian networks are directed acyclic graphs (DAGs) that represent probabilistic dependencies among a set of random variables [15, 16]. Each node in the graph corresponds to a variable, and the edges represent conditional dependencies. The strength of these dependencies is quantified using conditional probability distributions. The foundation of Bayesian networks lies in Bayes' theorem, which describes the conditional probability of an event based on prior knowledge of related conditions [17, 18].

Bayes' theorem is expressed as:

$$P(E|F) = \frac{P(F \mid E)P(E)}{P(F)}$$

where:

- P(E|F) is the probability of event E given that event F has occurred.
- P(F|E) is the probability of event F given that event E has occurred.
- P(E) and P(F) are the marginal probabilities of events E and F, respectively.

Bayesian networks have found applications in diverse fields, including social sciences (e.g., [19], banking [18] for credit scoring, and decision support systems [20, 21], etc.

Model Variables and Definitions

This study aims to predict teacher self-efficacy using the following key variables, derived from relevant literature:

- Self-Efficacy: A teacher's belief in their capacity to execute behaviors necessary to achieve specific teaching outcomes [2].
- Experience: Accumulated professional experience, influencing self-assessment of abilities [12]
- Burnout: A psychological syndrome characterized by emotional exhaustion, depersonalization, and reduced personal accomplishment (American Psychiatric Association) [22-24].
  - Emotional Exhaustion: Feelings of being emotionally overextended and depleted by work [23].
  - Depersonalization: A detached or cynical attitude towards recipients of one's service [25].
  - Accomplishment: A sense of competence and achievement in one's work [26].
- Attitude: A teacher's disposition and approach towards their work and students.
- Training: Professional development and educational qualifications [27].

Burnout, a multifaceted construct, is modeled as a composite variable derived from emotional exhaustion, depersonalization, and accomplishment.

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Bayesian Network Implementation

The Bayesian network for self-efficacy prediction is formulated as:

$$P(E|E_p, E_x, A_t, F_o) = \frac{P(A_t|E)P(E_x|E)P(E_p|E)P(F_o|E)P(E)}{P(A_t)P(E_x)P(E_p)P(F_o)}$$

where:

- $P(E|E_p, E_x, A_t, F_o)$ is the probability of self-efficacy knowing information on burnout, attitudes, work experience and training.
- $P(A_t|E)$ is the probability that the attitudes are observed given the self- efficacy.
- $P(E_x|E)$ is the probability that professional experience is observed given the self-efficacy.
- $P(E_p|E)$ is the probability that burnouts are observed given the self-efficacy.
- $P(F_o|E)$ is the probability that trainings are observed given the self-efficacy.
- P(E) is the marginal probability of the self-efficacy.
- $P(A_t)$ is the marginal probability of attitudes.
- $P(E_x)$ is the marginal probability of professional experience.
- $P(E_p)$ is the marginal probability of burnouts.
- $P(F_o)$ is the marginal probability of training history.

Marginal probabilities [28], such as P(Attitude), are calculated using the following formula:

P(Xi)=yj∑f(xi,yj)

where f(xi,yj) represents the joint probability distribution of variables X and Y.

Furthermore, this study extends to predicting collective efficacy, reflecting the overall sense of efficacy within an institution or department, acknowledging the influence of environmental factors [7].

The Bayesian network graph, visually representing the relationships between variables, is constructed using established principles [15, 16]**.** The aGrUM (A Graphical Universal Model) C++ library [29, 30] is employed for Bayesian network implementation and probability computation.

Data Collection and Analysis

Data for this study were collected through a survey administered to secondary school teachers between April 22 and May 10, 2024. The survey instrument, comprising approximately twenty questions, was designed to gather information on the variables outlined in Section 2.2. Random sampling was used to ensure representativeness.

The collected data will be used to estimate the conditional probability tables within the Bayesian network. The estimated probabilities will then be used to predict the teachers individual and collective self-efficacy.

RESULTS AND DISCUSSION

Data Overview and Preprocessing

A survey was conducted among 50 secondary school teachers in N'Djamena, Chad, with a robust response rate of 95%, resulting in 44 completed questionnaires. Following data preprocessing, the analysis focused on the following variables: emotional exhaustion, burnout, attitude, accomplishment, experience, training, and depersonalization.

Variable Dependencies and Bayesian Inference

The analysis revealed significant dependencies between several variables, notably burnout, accomplishment, depersonalization, and emotional exhaustion. These dependencies, as highlighted by [15, 31], underscore the

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interconnected nature of the factors influencing teacher self-efficacy. These relationships are visually represented in the Bayesian network graphs (Figures 1 and 2).

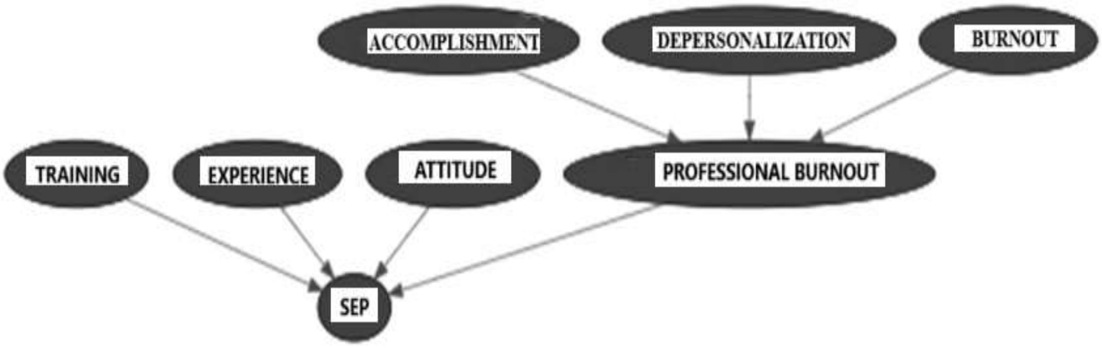

Figure 1 : Deduction system graph

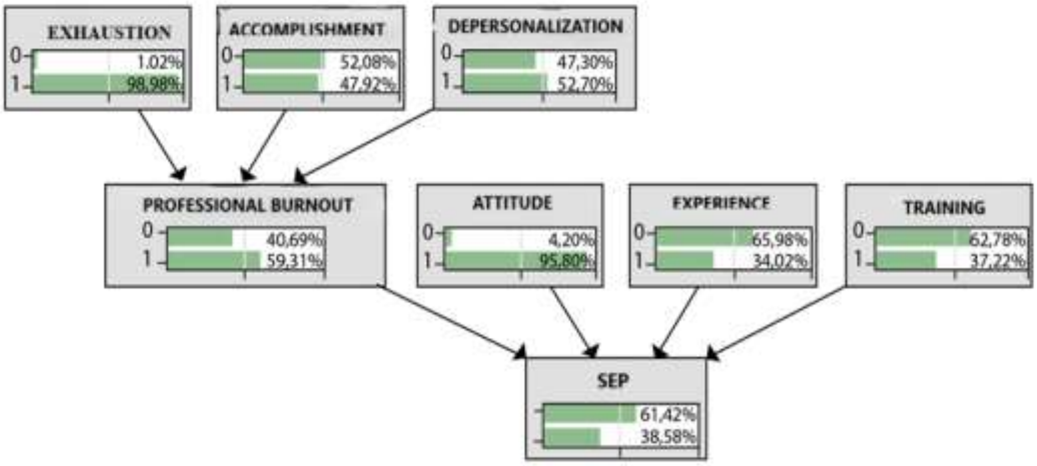

Figure 2: Prediction of a teacher's self-efficacy feeling

Applying the developed Bayesian network model to the survey data yielded valuable insights into both individual teacher self-efficacy and overall institutional efficacy. Figure 2 illustrates the Bayesian inference for individual self-efficacy, while Figure 3 presents the aggregated inference for overall efficacy, derived from the average individual self-efficacy scores.

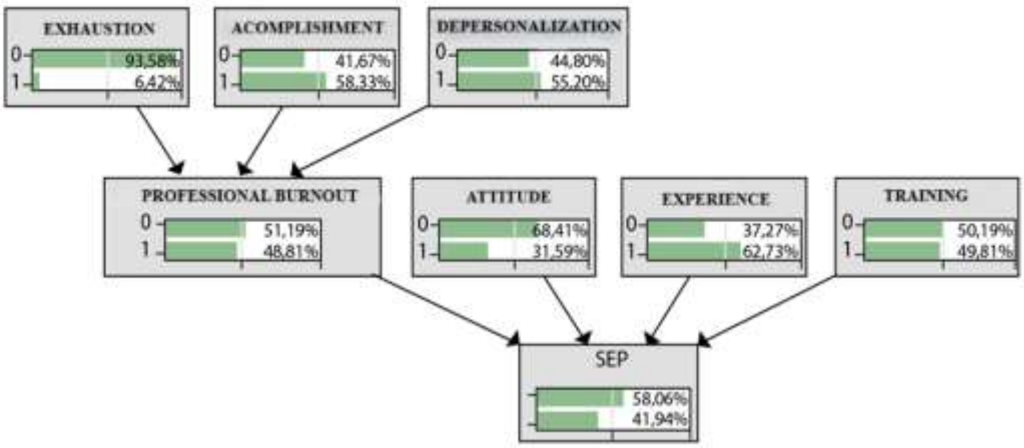

Figure 3: Bayesian inference of the overall efficacy feeling prediction system

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Key Findings and Interpretation

The analysis of individual variables revealed the following key findings:

- Emotional Exhaustion: A substantial 93.58% of respondents reported experiencing emotional exhaustion, potentially exacerbated by the survey's timing towards the end of the academic year.
- Accomplishment: 58.33% of teachers reported a sense of accomplishment in their work.
- Depersonalization: A significant 55.20% of respondents indicated feelings of depersonalization.
- Burnout: 51.19% of teachers did not experience burnout (indicating 48.81% experienced burnout).
- Attitude: Only 31.59% of teachers maintained a consistent positive attitude throughout the year.
- Experience: 62.73% of respondents were experienced teachers.
- Training: 49.81% of respondents had received pedagogical training.
- Self-Efficacy: A concerning 58.06% of teachers reported low self-efficacy, with only 41.94% reporting high self-efficacy. The low percentage of positive attitude directly impacts the self-efficacy result.

The low self-efficacy rates, in conjunction with the high emotional exhaustion and depersonalization, indicate a need for targeted interventions to support teachers in this specific context.

Influence of Variable Reduction

The impact of reducing the number of predictive variables on self-efficacy estimation was also explored (Figure 3 and figure 4). As shown in Figure 3, reducing the number of factors influences the predicted self-efficacy score. Specifically, when three factors were considered, the self-efficacy rate was 43.34%, compared to 41.94% when all factors were included. This demonstrates that the inclusion of more variables can slightly change the output of the model.

Comparison with Existing Literature

This study's findings can be contextualized within existing research on teacher self-efficacy. For example, [9] utilized multiple regression models to predict self-efficacy with a reduced number of variables. However, direct comparison is challenging due to variations in data and study environments.

Similarly, [10] employed a subjective Bayesian model, incorporating A Priori Probability Quotient (APRIQ) and likelihood ratios, to predict self-efficacy. Again, the differences in methodology and data limit the scope for direct comparison.

While direct comparisons are difficult, the current study expands upon existing research by incorporating a comprehensive set of personal characteristics within a Bayesian network framework. This approach offers a more nuanced and context-specific understanding of teacher self-efficacy.

Limitations and Future Directions

This study is subject to certain limitations. The sample size, while adequate, could be expanded for greater generalizability. Furthermore, the cross-sectional nature of the survey limits the ability to establish causal relationships. Future research could explore longitudinal data to examine the dynamic interplay between the studied variables and teacher self-efficacy. Future studies could also include control groups for more accurate results.

In conclusion, this study provides valuable insights into the factors influencing teacher self-efficacy in N'Djamena, Chad. The Bayesian network model offers a robust tool for predicting self-efficacy and informing targeted interventions to support teacher well-being and effectiveness.

CONCLUSIONS

This study successfully developed and applied a Bayesian network model to predict teacher self-efficacy, a critical factor influencing pedagogical effectiveness. The model effectively integrates a range of teacher characteristics, including educational background, professional experience, training, attitudes, and burnout indicators, to provide a probabilistic estimate of self-efficacy. This approach offers a significant advancement over traditional methods by capturing the complex interplay of factors contributing to a teacher's belief in their ability to succeed.

The model's versatility allows for both individual and collective self-efficacy prediction, enabling educational administrators to assess the overall efficacy of their teaching staff. The application of this model to survey data from secondary school teachers in N'Djamena, Chad, demonstrated its practical utility and yielded promising results, highlighting the potential for this tool to inform targeted interventions and support teacher development.

The ability to accurately predict teacher self-efficacy holds significant implications for educational management. By identifying teachers with low self-efficacy, administrators can implement tailored professional development programs, provide mentorship opportunities, and address systemic factors contributing to burnout and depersonalization. This proactive approach can enhance teacher well-being, improve classroom effectiveness, and ultimately contribute to better student outcomes.

Future research should focus on refining the model's predictive accuracy and expanding its applicability. Integrating machine learning techniques, such as deep learning or reinforcement learning, could enhance the model's ability to learn complex patterns and adapt to evolving educational contexts. Longitudinal studies are also recommended to examine the dynamic relationship between teacher characteristics and self-efficacy over time. Furthermore, investigating the model's performance in diverse cultural and educational settings would broaden its generalizability.

In conclusion, this research provides a valuable tool for educational stakeholders to understand and predict teacher self-efficacy. By leveraging the power of Bayesian networks, this model contributes to a more data-driven and evidence-based approach to teacher management, ultimately fostering a more supportive and effective learning environment for students.

Conflicts of Interest

The authors declare no conflicts of interest".

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