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The Effect of Deep Learning-Based Learning Pattern Analysis Using the LSTM Algorithm and Motivation on Mastery of Sequences and Series Material Among Vocational High School Students

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Abstract
This study aims to identify students' learning patterns on sequences and series using a deep learning approach based on the Long Short-Term Memory (LSTM) algorithm, and to analyze the influence of learning patterns and learning motivation on material mastery. The study uses a quantitative approach with an explanatory design, where data analysis is carried out through LSTM modeling for learning pattern classification and Partial Least Squares-Structural Equation Modeling (PLS-SEM) to test the structural relationships between variables. The results show that LSTM based learning patterns have a positive and significant effect on material mastery ($\beta = 0.294$; $t = 3.160$; $p = 0.002$), learning motivation has a stronger influence on material mastery ($\beta = 0.672$; $t = 7.038$; $p < 0.001$), and LSTM-based learning patterns have a very significant effect on learning motivation ($\beta = 0.803$; $t = 24.065$; $p < 0.001$) which indicates the presence of partial mediation. In conclusion, the integration of deep learning-based learning pattern analysis and motivational factors can strongly explain variations in mastery of sequence and series material in vocational school students, with high model predictive ability ($R^2 = 0.856$; Q^2predict = 0.693).

Keywords: Deep learning; Long Short-Term Memory (LSTM); learning motivation; mastery of sequences and series

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INTRODUCTION

The rapid development of artificial intelligence (AI) has significantly reshaped contemporary educational practices. AI technologies enable data-driven decision-making processes that support personalized learning environments, adaptive assessment, and predictive learning analytics. UNESCO, (2023) emphasizes that the integration of AI in education has the potential to improve instructional personalization, increase assessment efficiency, and provide early prediction of students' academic performance. These developments highlight the growing importance of intelligent learning systems capable of analyzing large-scale educational data to support more effective teaching and learning processes.

In Indonesia, this technological transformation is particularly relevant in vocational education. Vocational high schools (Sekolah Menengah Kejuruan/SMK) are expected to prepare students with competencies aligned with rapidly evolving technological and industrial environments. However, international assessments reveal that students' mathematical literacy remains a critical challenge. The Program for International Student Assessment (PISA) 2022 reports that Indonesian students' mathematics performance is still below the international average (OECD, 2023). This condition suggests that conventional instructional approaches may not sufficiently support students in developing deep conceptual understanding and quantitative reasoning skills. Consequently, innovative learning strategies that integrate advanced technologies and data analytics are increasingly necessary to enhance mathematics education.

Recent advances in deep learning, a subfield of machine learning, have opened new opportunities for analyzing complex educational data. Deep learning models are capable of extracting hierarchical representations from high-dimensional datasets and modeling nonlinear relationships that are difficult to capture through traditional analytical approaches. A comprehensive review conducted by Mienye and Swart (2024) indicates that the rapid development of deep neural network architectures including recurrent neural networks, transformer models, and hybrid architectures has significantly expanded the application of deep learning in large-scale data analytics. In addition, comparative analyses demonstrate that deep learning models often outperform traditional machine learning algorithms in capturing complex patterns within unstructured and sequential datasets (Shiri et al., 2024).

Within the field of education, these developments have contributed to the emergence of learning analytics and educational data mining, which utilize digital traces of students' learning activities to better understand learning processes. Behavioral learning data, such as frequency of accessing learning materials, interaction duration, and task completion patterns, provide valuable insights into students' engagement and learning strategies (Gašević et al., 2019). The analysis of such behavioral data allows researchers and educators to develop predictive models capable of identifying learning difficulties and supporting timely pedagogical interventions.

Among various deep learning techniques, Long Short-Term Memory (LSTM) networks have gained particular attention for analyzing sequential learning data. LSTM is a variant of recurrent neural networks specifically designed to capture long-term dependencies in time-series data. Recent surveys on deep learning methodologies highlight that LSTM models demonstrate strong performance in modeling sequential patterns due to their ability to preserve relevant information over extended sequences (Tian et al., 2025). In educational settings, this capability makes LSTM highly suitable for analyzing learning log data generated through digital learning platforms, where students' interactions occur sequentially over time.

The application of AI has also begun to influence research in mathematics education, particularly in analyzing students' learning behaviors and predicting learning outcomes. AI-driven learning analytics can provide insights into how students interact with mathematical content, identify learning patterns, and support the development of adaptive instructional systems. Such approaches are especially valuable in mathematics learning, which often requires sustained cognitive engagement and structured reasoning processes.

Despite the growing interest in applying AI to education, several important research gaps remain. First, a conceptual gap exists between technological approaches and psychological perspectives in explaining students' learning outcomes. Many AI-based studies focus primarily on predicting academic performance without considering psychological factors that influence learning behavior. For example, Ali Eli et al., (2025) demonstrated that deep neural network models can improve the accuracy of predicting students' academic performance; however, the study did not incorporate motivational constructs that may explain variations in learning engagement.

Second, there is a methodological gap related to the integration of behavioral learning data with psychological constructs. Some studies have attempted to develop adaptive learning systems using machine learning techniques. Research Huang et al.,

(2020) proposed a clustering-based recommendation system for adaptive learning, yet the model did not integrate motivational variables that may influence students' engagement with learning systems. Meanwhile, research in educational psychology consistently highlights the crucial role of motivation in shaping students' academic engagement and persistence.

Learning motivation is widely recognized as a key determinant of academic success. According to Self-Determination Theory, students' motivation is influenced by the satisfaction of three basic psychological needs: autonomy, competence, and relatedness (Ryan & Deci, 2020). When these needs are fulfilled, students tend to exhibit higher levels of cognitive engagement and persistence in challenging learning tasks. Empirical studies also demonstrate that intrinsic motivation is positively associated with mathematics achievement and negatively associated with mathematics anxiety (OECD, 2023). Furthermore, the development of academic interest over time can strengthen students' self-efficacy and engagement in mathematical problem solving (Hidi & Renninger, 2019).

Third, there is a contextual gap in the application of AI-driven learning analytics within vocational mathematics education. Most existing studies are conducted in general academic contexts rather than vocational education settings. However, vocational education presents unique challenges because students often demonstrate diverse academic backgrounds and varying levels of conceptual readiness. In mathematics learning, conceptual mastery is particularly important in topics that involve pattern recognition and quantitative reasoning.

One such topic is sequences and series, which play a fundamental role in mathematical reasoning and problem solving. Understanding sequences and series requires students to recognize patterns, construct generalizations, and apply mathematical structures to various quantitative problems. Recent studies indicate that students' conceptual understanding of sequences and series significantly influences their ability to solve complex mathematical problems (Susmina & Marlina, 2024). Moreover, this topic contributes to the development of mathematical representation and reasoning skills that underpin quantitative analysis (Afifah et al., 2024). The concepts of sequences and series also have practical applications in modeling growth patterns and recurring numerical phenomena (Harun et al., 2024). Therefore, improving students' mastery of this topic requires innovative analytical approaches capable of capturing both behavioral learning patterns and psychological determinants of learning.

To address these research gaps, this study integrates deep learning-based learning pattern analysis with learning motivation constructs to explain students' conceptual mastery in mathematics learning. Specifically, this study focuses on identifying students' learning patterns in sequences and series using the Long Short-Term Memory algorithm and examining how these patterns interact with motivational factors to influence learning outcomes.

This study proposes a conceptual framework that combines behavioral learning analytics derived from deep learning models with psychological constructs measured through motivational instruments. The relationships among these constructs are examined using Partial Least Squares Structural Equation Modeling (PLS-SEM), which allows the simultaneous evaluation of predictive relationships among latent variables.

Based on the theoretical framework, the following hypotheses are proposed: Deep learning-based analysis of students' learning patterns has a significant effect on students' mastery of sequences and series. Learning motivation has a significant positive effect on students' mastery of sequences and series. Deep learning-based learning pattern analysis significantly influences students' learning motivation. Deep learning-based learning patterns and learning motivation simultaneously influence students' mathematics learning outcomes.

This study contributes to the literature in two important ways. From a theoretical perspective, it advances research in educational data science by integrating deep learning techniques with motivational constructs within a unified empirical framework. From a practical perspective, the findings provide insights for developing AI-based learning analytics systems that support adaptive learning and early prediction of students' learning difficulties. Such systems can help educators design more personalized and data-driven instructional strategies, particularly in vocational mathematics education where students' learning characteristics are highly diverse.

METHODS

This study employed a quantitative explanatory research design to examine causal relationships among variables using inferential statistical analysis. The explanatory approach was chosen because the study aims not only to describe phenomena but also to empirically analyze the influence of independent variables on a dependent variable within a structured conceptual framework (Creswell & Creswell, 2024). The research model investigates the effects of Deep Learning-based learning pattern analysis (X_1) and learning motivation (X_2) on students' mastery of sequences and series (Y). Structural relationships among variables were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is appropriate for predictive modeling and theory testing involving latent constructs.

The population consisted of all eleventh-grade students at a vocational high school (SMK). Sampling was conducted using probability sampling with a simple random sampling technique, ensuring equal selection opportunities for all population members (Fraenkel et al., 2019). A total of 100 students were selected as respondents. This sample size satisfies the minimum requirement for PLS-SEM analysis based on the 10-times rule and is adequate considering the complexity of the structural model (Hair et al., 2024). Respondents were randomly selected using the official school attendance list to maintain objectivity and reduce selection bias.

Data were collected from three primary sources: Learning Management System (LMS) activity logs, a learning motivation questionnaire, and a mathematics mastery test. LMS log data captured students' learning behaviors, including frequency of accessing materials, learning duration, task completion, formative and summative assessment scores, and attendance records. The use of LMS data aligns with the learning analytics approach, which utilizes digital learning traces to analyze student learning behaviors (Romero & Ventura, 2020). These data were analyzed using the Long Short-Term Memory (LSTM) algorithm to identify sequential learning patterns during the learning process (Wang et al., 2023).

Learning motivation was measured using a five-point Likert scale questionnaire developed based on Self-Determination Theory (SDT), which emphasizes the role of autonomy, competence, and relatedness in shaping student engagement and persistence in learning (Deci & Ryan, 2017; Jia et al., 2025). The instrument also incorporated perspectives from social-cognitive motivation theory, particularly the roles of self-efficacy and self-regulated learning (Schunk & DiBenedetto, 2020). The questionnaire consisted of 30 items measuring intrinsic motivation, extrinsic motivation, academic self-efficacy, self-regulated learning, learning persistence, and academic anxiety. Content validity was evaluated through expert judgment, while construct validity and reliability were assessed using PLS-SEM with SmartPLS 4. Measurement model evaluation followed standard criteria: outer loading ≥ 0.70, Average Variance Extracted (AVE) ≥ 0.50, and Composite Reliability ≥ 0.70, indicating adequate convergent validity and internal consistency (Hair et al., 2024; Sarstedt et al., 2024).

Students' mastery of sequences and series was measured using a 25-item multiple-choice test developed according to the revised Bloom's Taxonomy at the cognitive levels of understanding, application, and analysis (C2-C4). The test covered arithmetic sequences, arithmetic series, geometric sequences, and geometric series in both procedural and contextual problem formats. Item validity was examined using product-moment correlation, and reliability was assessed using Cronbach's Alpha to determine internal consistency. Reliability is essential in educational assessment because it indicates the consistency of measurement results (Arbeni et al., 2025). Recent research also highlights the importance of psychometric evaluation to ensure accurate measurement outcomes (Edelsbrunner et al., 2025; Guilarte et al., 2025). Items that did not meet validity criteria were removed prior to further analysis.

The research procedure consisted of several stages: research planning, data collection, data preprocessing, and data analysis. The planning stage included literature review, instrument development, and research approval from the school. Data collection involved extracting LMS log data, administering the motivation questionnaire, and conducting the mathematics mastery test. LMS data then underwent preprocessing steps including data cleaning, normalization, and numerical transformation to construct sequential datasets. The LSTM model was trained using Python with TensorFlow and Keras libraries to identify learning patterns. The resulting classification outputs were converted into numerical values for further statistical analysis. Structural relationships among variables were subsequently tested using SmartPLS 4.0.

Data analysis consisted of descriptive and inferential stages. Descriptive analysis summarized the data using mean values, standard deviations, and frequency distributions to provide an overview of the dataset (Creswell & Creswell, 2024). Inferential analysis was conducted using PLS-SEM, which is suitable for analyzing complex relationships among latent variables without strict normality assumptions (Sarstedt et al., 2024). Model evaluation included measurement model assessment (convergent validity, discriminant validity using the HTMT < 0.90 criterion, and construct reliability) and structural model assessment using the coefficient of determination (R^2) and predictive relevance (Q^2). The significance of structural relationships was tested using a bootstrapping procedure at a 5% significance level to obtain stable parameter estimates (Hair et al., 2024).

To ensure the robustness of the findings, several validation procedures were conducted. Construct validity and reliability were assessed through outer model evaluation, discriminant validity was tested using HTMT, and the model's predictive capability was evaluated through Q^2 predictive relevance. Parameter stability was further examined using bootstrapping. Data processing involved Python for deep learning modeling, Microsoft Excel for preliminary data management, and SmartPLS 4.0 for PLS-SEM analysis. The integration of artificial intelligence techniques with multivariate statistical analysis enables a comprehensive examination of factors influencing students' mastery of mathematical concepts.

RESULTS & DISCUSSION

The following presents the research findings in a systematic, objective manner based on empirical data analysis obtained through data processing and statistical testing stages in accordance with the established research design. The results are presented through descriptive and inferential analyses by displaying the main relevant statistical indicators. A summary of the findings is provided in tables to support interpretation and to serve as the basis for the theoretical discussion in the subsequent section.

Results

Analysis of Google Classroom activity logs using the Long Short-Term Memory (LSTM) model produced the following classification of students' learning patterns on the topic of sequences and series:

Table 1. Distribution of Students' Learning Pattern Category

Learning Pattern Category	Amount	Percentage
Reflective	43	43%
Creative–Contextual	27	27%
Collaborative	25	25%
Critical–Exploratory	5	5%
Low Awareness	0	0%
Total	100	100%

Descriptive statistics show a Mean = 3.93, SD = 0.852, and Skewness = –0.357. The distribution is negatively skewed toward higher categories, indicating that most students demonstrate relatively structured and adaptive learning patterns. The majority of students (70%) fall within the reflective and creative–contextual categories. No students were found in the lowest category. This finding indicates the effectiveness of the digital learning system in fostering consistent learning behaviors.

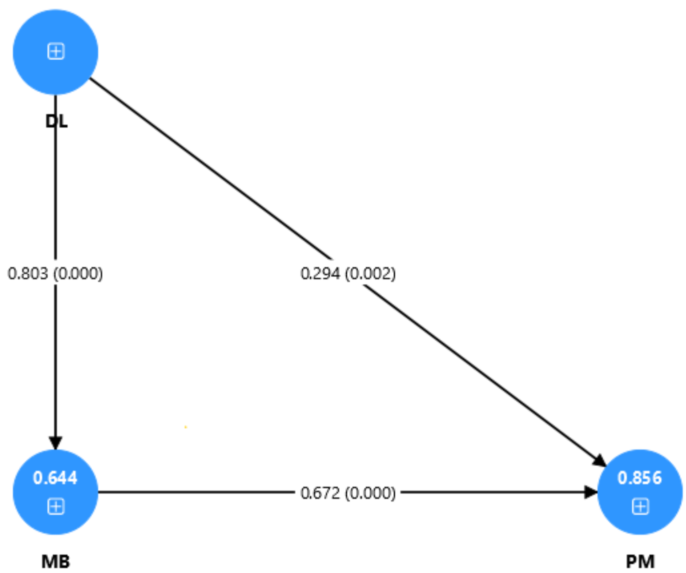

Figure 1. PLS Algorithm Iteration Results for Structural Model (inner model)

The results of the PLS-SEM analysis indicate that Deep Learning–based learning patterns have a significant effect on mastery of sequences and series.

Table 2. Effect of Learning Patterns on Subject Mastery

Relationship	Coefficient (β)	t-statistic	p-value	Description
$X_1 \rightarrow Y$	0,294	3,16	0,002	Significant

A β value of 0.294 indicates a direct effect in the moderate category. This means that the more consistent students' learning activity patterns in the LMS, the higher the level of subject mastery achieved.

Learning motivation has the most dominant influence on subject mastery.

Table 3. Effect of Learning Motivation on Subject Mastery

Relationship	Coefficient (β)	t-statistic	p-value	Description
$X_2 \rightarrow Y$	0,672	7,038	0.000	Highly Significant

A coefficient of 0.672 indicates a strong effect. In other words, intrinsic motivation and learning engagement make the greatest contribution to students' success in understanding sequences and series. Descriptive statistics for motivation show average item scores ranging from 3.66 to 3.87, a median of 4, and SD values between 0.78 and 0.92. The distribution is relatively homogeneous and falls within the high category.

The structural model demonstrates very high explanatory power.

Table 4. Coefficient of Determination

Endogenous Variable	R^2	Interpretation
Learning Motivation	0,644	Strong
Subject Mastery	0,856	Very Strong

An R^2 value of 0.856 indicates that 85.6% of the variance in subject mastery can be explained by the combination of Deep Learning–based learning patterns and learning motivation.

In addition, the analysis results reveal a significant relationship between X_1 and X_2, with a path coefficient (β) of 0.803 and a p-value of 0.000, indicating a positive and statistically very strong effect. This finding confirms that digital learning patterns substantially contribute to increasing students' learning motivation. Furthermore, motivation acts as a partial mediator that strengthens the impact of digital learning patterns on subject mastery. Structurally, this indicates that the relationships among variables are not only direct but also operate through a significant mediating mechanism.

Discussion

The LSTM-based classification results indicate that most students fall into the reflective (43%) and creative-contextual (27%) categories, with a mean score of 3.93, suggesting a relatively high tendency in learning patterns. These findings indicate that vocational high school students tend to demonstrate structured and adaptive learning behaviors when studying sequences and series within a digital learning environment. Theoretically, this result aligns with the self-regulated learning (SRL) framework, which emphasizes planning, monitoring, and reflection as key processes in autonomous learning. In digital learning contexts, advances in learning analytics allow self-regulation to be measured not only through students' perceptions but also through digital learning traces recorded in online learning systems. The use of Long Short-Term Memory (LSTM) models enables the identification of temporal learning behavior patterns due to their ability to process sequential data and capture long-term dependencies. Previous studies have demonstrated that LSTM-based models can improve the accuracy of academic performance prediction (Al-Azazi & Ghurab, 2023). Other research has shown that integrating LSTM with deep learning architectures such as CNN–LSTM further enhances prediction accuracy in digital learning environments (Arya, 2024). Moreover, LSTM has been applied in the development of adaptive learning recommendation systems capable of predicting students' learning needs based on digital interaction patterns (Yazdi et al., 2024). More recent studies have also introduced Bi-LSTM models combined with SHAP interpretability techniques to increase transparency in learning analytics models and identify key behavioral factors influencing academic performance (Kalita et al., 2025). These findings suggest that integrating deep learning with learning analytics enables a more objective and predictive analysis of student learning behaviors compared with conventional survey-based approaches.

Structural model analysis shows that Deep Learning-based learning patterns have a positive and significant effect on subject mastery, with a path coefficient of 0.294 ($p = 0.002$). This result indicates that consistent engagement with digital learning activities contributes to students' academic achievement. The finding is consistent with learning analytics literature showing that the frequency and quality of interactions within a Learning Management System (LMS) are positively associated with academic performance (Ifenthaler & Yau, 2020). However, the moderate effect size suggests that digital learning behavior alone is not the sole determinant of learning outcomes. Conceptually, this supports the multidimensional perspective of learning, which highlights the interaction between cognitive, affective, and environmental factors in shaping academic achievement. Compared with traditional regression-based studies that often show limited explanatory power, the use of actual log data and sequential LSTM modeling in this study allows for a more dynamic analysis by capturing students' learning activities over time.

Furthermore, the results indicate that learning motivation has the strongest influence on subject mastery, with a path coefficient of 0.672 ($p < 0.001$). This finding is consistent with Self-Determination Theory (SDT), which posits that intrinsic motivation enhances cognitive engagement, persistence, and depth of academic understanding (Ryan & Deci, 2020). The relatively high level of student motivation observed in this study suggests that basic psychological needs such as autonomy and competence are relatively well supported within the digital learning environment. Mechanistically, motivation functions as a psychological mediator that transforms learning activities into cognitive achievement. This result also aligns with the meta-analysis conducted by Howard et al., (2021), which demonstrates a significant relationship between motivation and mathematics achievement. Importantly, this study extends previous findings by demonstrating that motivation functions not only as an independent predictor but also as a mediating variable between digital learning behavior and subject mastery.

Simultaneous analysis reveals that the combination of Deep Learning-based learning patterns and learning motivation explains 85.6% of the variance in subject mastery ($R^2 = 0.856$). This value indicates a very high explanatory power within the context of educational research. The identified partial mediation structure suggests that the influence of digital learning behavior on subject mastery occurs largely through increased learning motivation. This finding aligns with the social-cognitive perspective, which emphasizes that environmental factors, including educational technologies, influence learning outcomes through students' internal psychological processes (Schunk & DiBenedetto, 2020). In other words, digital technology does not directly determine learning outcomes but rather operates through motivational mechanisms that enhance student engagement.

From a theoretical perspective, this study contributes to the integration of three major approaches: computational modeling using LSTM, educational psychology emphasizing intrinsic motivation, and causal analysis using PLS-SEM. This integration enables analyses that are not only computationally predictive but also psychologically interpretable and methodologically robust. Consequently, the findings contribute to the development of AI-informed educational theory, particularly in explaining how artificial intelligence techniques can be integrated with psychological constructs to understand the relationships between digital learning behaviors, motivation, and academic achievement.

Despite these contributions, several limitations should be acknowledged. First, the sample size is relatively limited and drawn from a single educational institution, which may restrict the generalizability of the findings. Second, the relatively high distribution of subject mastery scores (SD = 5.53) indicates the possibility of a ceiling effect, which may reduce data variability and influence the strength of structural estimates. Third, the behavioral data used in this study were derived solely from LMS activity logs, which may not fully capture the broader learning experiences of students outside the digital system.

Future research should therefore involve larger and more diverse samples across multiple schools or regions to enhance external validity. Additionally, the development of hybrid deep learning models, such as CNN-LSTM or transformer-based architectures, may further improve the predictive capability of learning analytics models. Future studies may also integrate multimodal learning analytics data, including online discussion interactions, text analysis, or affective learning indicators, to provide a more comprehensive understanding of the relationships between digital learning behaviors, motivation, and academic success in mathematics learning.

CONCLUSION

This study examined students' learning patterns in sequences and series using an LSTM-based Deep Learning approach and analyzed the effects of learning patterns and motivation on subject mastery. The findings demonstrate that students' digital learning behaviors can be effectively identified through LMS activity logs, revealing dominant reflective and creative-contextual learning patterns. These results indicate that learning activities in digital environments exhibit structured and consistent behavioral patterns that can be modeled computationally. The structural analysis shows that learning patterns significantly influence subject mastery, while learning motivation emerges as the strongest predictor of academic achievement and acts as a mediator between digital learning behavior and learning outcomes. These findings highlight that digital learning technologies not only enable the detection of students' behavioral patterns but also strengthen motivational processes that support cognitive achievement. Overall, this study contributes to the integration of learning analytics, educational psychology, and artificial intelligence by demonstrating how deep learning models can support predictive and explanatory analyses of student learning dynamics in digital mathematics education.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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