The object of this research is to focus on the Pro Growth Constructive Interaction (PGCI) approach as a strategy to improve lecturer performance. PGCI integrates multidimensional interactions involving academic, social, technological, individual, external and temporal dimensions to achieve optimal productivity and efficiency. In this research, there is a main problem to be addressed, namely identifying and optimizing the factors that influence lecturer performance by developing a comprehensive model that is able to predict and improve performance through multidimensional interactions. The research results obtained were the dimension contribution showing the highest contribution to lecturer performance (0.177062), followed by the technological (0.174122), social (0.167044), external (0.165670), and individual (0.163610) dimensions). In the results of the mathematical model with the Lagrangian method optimized with a machine learning algorithm distributing weights with a focus on external dimensions (0.2650) and technology (0.2179), resulting in a performance increase of 7.35 %. This model is able to achieve an accuracy of 92.4 % in predicting lecturer performance using a deep neural network algorithm. In this research, there is a brief interpretation of the research findings showing that the temporal and technological dimensions have an important role in determining lecturer performance. By prioritizing these two dimensions, the optimized model yields significant improvements. Characteristics obtained from research, multidimensional analysis covering various aspects of performance and high accuracy and measurable performance improvements prove the reliability of the model. The results of this research have significant practical applications in higher education institutions

Keywords: lecturer performance optimization, mathematical model, deep neural network, accuracy, education

UDC 28.17

DOI: 10.15587/1729-4061.2025.322723

DEVELOPMENT OF TRANSFORMATION OF LECTURER PERFORMANCE THROUGH PRO GROWTH CONSTRUCTIVE INTERACTION WITH A MULTIDIMENSIONAL APPROACH AND MACHINE LEARNING BASED MATHEMATICAL MODELS

Julfansyah Margolang
Master of Management*

Yeni Absah
Corresponding author
Doctor in Management*
E-mail: yeni.absah@usu.ac.id

Sirojuzilam Hasyim
Professor of Economy*

Parapat Gultom
Doctor of Industrial Systems Engineering*

*Department of Economics and Business
Universitas Sumatera Utara
Dr. T. Mansur str., 9, Padang Bulan,
North Sumatera, Indonesia, 20222

Received 22.11.2024
Received in revised form 22.01.2025
Accepted date 07.02.2025
Published date 27.02.2025

How to Cite: *Margolang, J., Absah, Y., Hasyim, S., Gultom, P. (2025). Development of transformation of lecturer performance through pro growth constructive interaction with a multidimensional approach and machine learning based mathematical models. Eastern-European Journal of Enterprise Technologies, 1 (2 (133)), 43–52. https://doi.org/10.15587/1729-4061.2025.322723*

1. Introduction

At this time, improving lecturer performance is a strategic issue in the context of higher education development that is very necessary [1]. In this case, lecturer performance not only impacts the quality of education, but also the reputation of the university as a whole. In the current era of technological and information development, lecturers are faced with increasingly complex challenges and problem such as improving the quality of learning, research innovation and community service [2, 3]. To answer problems and challenges, a new approach is needed that can encourage holistic and sustainable transformation of lecturer performance [4]. One relevant approach is to utilize Pro Growth Constructive Interaction (PGCI) using a multidimensional approach and machine learning-based mathematical models. Pro Growth Constructive Interactions (PGCI) is part of a framework designed to create constructive interactions that support individual and organizational growth [5]. In this section there is a lecturer performance. PGCI aims to build a work environment that is collaborative, innovative and responsive to change [6]. The PGCI concept will emphasize the importance of interactions that are not only horizontal between lecturers, but also vertical between lecturers and other stakeholders, such as students, institutional leaders and the community [7]. In this way, PGCI is able to create an ecosystem that is conducive to improving lecturer performance in various dimensions, such as academic, social and technological dimensions. The multidimensional approach at PGCI highlights that lecturer performance cannot be assessed from one aspect alone, but must include various interconnected aspects [8, 9]. In this research, there are academic variables that have lecturers' abilities in teaching, research and scientific publications. Then there are social variables related to the lecturer's interpersonal communication with students, colleagues and the wider community, while for technological variables there the lecturer's ability to utilize digital technology to support learning, research and community service activities. Integration of these three variables is needed to create holistic and competitive lecturer performance. In the context of machine learning, the use of mathematical models is a promising approach to support PGCI implementation [10, 11]. Machine learning enables efficient processing of large amounts of data to identify patterns, analyze relationships and make accurate predictions. In the context of lecturer performance transformation, machine learning can be used to develop a more objective and data-based performance evaluation system. Apart from that, machine learning can also help in designing professional development programs that suit the individual needs of lecturers, based on in-depth data analysis [12, 13].

The problem in this research is resistance to change, both from individual lecturers and from the institution as a whole. The change in work paradigm required by PGCI requires a strong commitment from all parties to create a collaborative and innovative work culture [14]. Apart from that, limited technological infrastructure and digital skills of lecturers are also obstacles that need to be overcome to support the application of machine learning in transforming lecturer performance. To overcome these challenges, a comprehensive and integrated strategy is needed. This strategy includes developing lecturer capacity through training and workshops, providing adequate technological infrastructure, and strengthening a work culture that supports innovation. Apart from that, it is also important to involve lecturers in the planning and implementation process of PGCI, so that implementing PGCI with a multidimensional approach and machine learning has great potential to transform lecturer performance. For example, by utilizing interaction data between lecturers and students, institutions can identify factors that influence learning effectiveness [14, 15]. With the developed mathematical model, institutions can provide specific and evidence-based recommendations to lecturers to improve their performance. Apart from that, PGCI can also be used to identify opportunities for collaboration between lecturers and between institutions, which in turn can increase research productivity and innovation. In an effort to transform lecturer performance through PGCI, this research aims to develop a holistic and data-based framework. This research will include needs analysis, development of machine learning-based mathematical models, and evaluation of PGCI implementation in several higher education institutions. It is hoped that the results of this research can make a real contribution to improving the quality of higher education in Indonesia and at the global level [16, 17].

Therefore, research aimed at developing this and that becomes relevant because the transformation of lecturer performance through Pro Growth Constructive Interaction with a multidimensional approach and machine learning-based mathematical models is an innovative solution to answer the challenges of higher education in the digital era. With this approach, it is hoped that lecturers can optimize their potential, improve performance holistically, and contribute more to the progress of higher education so that the implementation of PGCI with the support of technology-based mathematical models and machine learning is a strategic step to realizing superior and competitive higher education.

2. Literature review and problem statement

Research [18] carries out market changes by adjusting business processes by applying seven parameters such as decision management, change management, organizational learning, business-oriented framework and business intelligence so as to illustrate the influence of flexibility on organizational effectiveness. Problems in this research that have not been resolved include the integration of Constructive Pro Growth with a multidimensional approach and the difficulty in implementing parameters for optimizing mathematical models with machine learning algorithms. This problem has not been resolved because in its application it is necessary to identify the most relevant factors and how to integrate them into a complex system and it is necessary to consider how the parameters that have been identified can be adapted to suit the model used. Based on this, it is necessary to apply machine learning techniques to be able to process parameter data and determine their influence on organizational effectiveness.

Research [19] tested strategic management so that it could assess the relationship between the risk management process and organizational management with the aim of measuring the parameters of good corporate governance, organizational flexibility and strategic change management. Unresolved problems such as changes in parameters and lack of correlation between risk management processes and organizational management make it difficult to determine good corporate governance and multidimensionality makes it difficult to capture patterns that interact and influence growth. This is an unresolved problem because it requires identifying the most relevant factors and how to integrate them into a complex system and determining parameters and correlations requires a technique or method that can process them, such as machine learning or the use of algorithms. Based on this, algorithms and machine learning are needed to determine the correlation between the risk management process and organizational management.

Research [20] will determine company performance in terms of company flexibility and management which produces rules in assessing the relationship between risk management processes and organizational management. The problems that have not been resolved are the absence of valid parameters used and the absence of variables that influence the determination of company performance and the need to identify the most relevant factors and how to integrate them into parameters so this has not been resolved because it is necessary to apply Pro Growth Constructive Interaction parameters with a multidimensional approach and optimization of mathematical models based on this will be proposed and resolved using the method of determining parameters and utilizing machine learning in determining variables so that determining company performance can run effectively.

Research [21] will apply organizational flexibility parameters that will explore managerial relationships in business management. In this regard it would be recommended that future contributions should emphasize guidelines for implementing flexibility while elaborating on flexibility theory. The findings presented in this paper have the potential to attract the attention of academics and practitioners to design ways to implement and improve organizational flexibility. There are problems that are still unresolved, including managerial variables that change with each assessment and it is difficult to identify the most relevant factors, then there is no optimization of the results, which gives rise to problems that are difficult to solve because to apply organizational flexibility parameters, Pro Growth Constructive Interaction parameters are needed and optimization of mathematical models with machine learning algorithms.

Research [22] states that constructive interactions between leaders and employees have a significant impact on improving performance in the work environment. These interactions allow for open communication, supportive collaboration, and support focused on achieving shared goals. The results of this research are relevant for improving lecturer performance through interactions that support professional and personal development, especially in the context of vocational higher education. However, there are problems that have not been resolved, such as interactions that are biased towards open communication and differences in goals, this has become an issue in unresolved problems because biased interactions can cause information failure which makes it difficult to improve performance. Based on this, machine learning algorithms will be utilized so that biased information does not occur due to open interactions in the system.

Research [23] discusses Pro Growth Constructive Interaction which focuses on interaction approaches that support individual growth and productivity in organizations. This approach emphasizes developing skills and competencies through positive and supportive interactions. These findings can be adapted in the context of higher education to help lecturers develop teaching, research and service skills with support from management and colleagues. There are unresolved problems such as the absence of parameters to assess the relationship between risk management processes and the absence of identification of the most relevant factors in Pro Growth Constructive Interactions, so a multidimensional approach can effectively capture the various aspects that interact with each other. This is an unresolved problem because there are no good governance communication rules according to standard procedures and the Pro Growth Constructive Interaction parameters have not been implemented as well as the implementation of parameters for optimizing mathematical models with machine learning algorithms. Based on this, a method will be implemented to support the formation of communication rules with machine learning algorithms to focus on optimization and application of Pro Growth Constructive Interaction parameters with multi-dimensionality.

Research [24] shows that training and professional development are important factors in improving academic performance in educational institutions. Appropriate training can help lecturers improve their competence and abilities, while support through constructive interactions can strengthen training results. There are problems that have not been resolved, such as there are still many variables that are difficult to integrate in the effectiveness of increasing competence and performance in the academic environment and there has been no implementation of the Pro Growth Constructive Interaction parameters with a multidimensional approach so this problem has not been resolved because it has not been possible to identify a multidimensional approach that can effectively capture various aspects that interact with each other and influence growth. Based on this, machine learning techniques will be utilized to be able to process many variables quickly and easily improve competence and performance in the academic environment as well as apply Pro Growth Constructive Interaction parameters with a multidimensional approach with mathematical optimization

Research [25] found that work culture in an organization influences the effectiveness of constructive interactions. Institutions that have an open and supportive work culture tend to be more successful in implementing constructive interactions that focus on growth. There are problems that are still unresolved, such as determining different work culture parameters in each institution and the difficulty in implementing Pro Growth Constructive Interaction parameters with a multidimensional approach. This is an unresolved problem because different work cultures find it difficult to implement constructive interactions which results in decreased organizational or institutional performance and it is necessary to identify the most relevant factors and how to integrate them into the system. Based on this, it is relevant for the Indonesian Aviation Polytechnic which needs to adapt its organizational culture to a Pro Growth approach, so that it can increase the overall productivity and performance of lecturers.

Research [26] shows that intrinsic motivation and social support play an important role in lecturer performance. When lecturers receive support from colleagues and superiors in the form of constructive interactions, they tend to have higher motivation to achieve optimal results. These findings emphasize the importance of proactive interactions that support growth, especially in the context of higher education where developing lecturer performance is the main key in improving the quality of education. There are unresolved problems such as the need for support in the form of proactive interactions that can help lecturers achieve maximum performance as well as the application of Pro Growth Constructive Interaction parameters with a multidimensional approach. This is an unresolved problem because communication can make it difficult to achieve proactive interaction so methods are needed that can overcome this, one of which is the use of Pro Growth and it requires identifying the most relevant factors and how to integrate them into a complex system.

Based on this, implementing parameters for optimizing mathematical models with machine learning algorithms can be a solution and application of a multidimensional approach.

3. The aim and the objectives of the study

The aim of this study is to identify lecturer performance through the application of Pro Growth Constructive Interaction with a multidimensional approach supported by machine learning-based mathematical models.

To achieve this aim, the following objectives are accomplished:

– to apply parameters to Pro Growth Constructive Interaction with a Multidimensional Approach;

– to implement of parameters for optimization of mathematical models with machine learning algorithms.

4. Materials and methods

In this research, there will be a research object, namely a focus on the Pro Growth Constructive Interaction (PGCI) approach as a strategy to improve lecturer performance. The main hypothesis of this research is the Effect of Pro Growth Constructive Interaction on Lecturer Performance and the Multidimensional Approach in Transforming Lecturer Performance as well as Mathematical and Machine Learning Models in Predicting Transformation of Lecturer Performance. The assumption in this work is that lecturers will have the capacity to make changes through constructive Pro Growth interactions which include lecturers being able to implement several methods to improve performance in the fields of teaching, research and community service. Then this research takes a multidimensional approach which will look at the factors that influence lecturer performance and mathematical models with machine learning algorithms will be used to be able to see patterns in the lecturer's performance process so that they can make accurate predictions. The simplifications adopted in the work include a focus on analysis of the complexity of interactions between variables such as teaching effectiveness, research productivity, and lecturers' academic contributions. Then there will be multidimensional which will combine many aspects such as research and service. Then a mathematical model will be built to see the patterns and relationships contained in the variables used with the aim of facilitating interpretation of the analysis results. The research steps gin with designing the system architecture as shown in Fig. 1 below.

Fig. 1 will explain how to apply multidimensional Lagrangian methods using mathematical models and machine learning that use deep neural network algorithms to identify and predict lecturer performance. In this section, the stages and formulations used in processing methods and algorithms described. The mathematical formulation in multidimensional is as follows:

$$K_i = f\left(A,S,T_e,I,E,T\right). \tag{1}$$

In (1) there is a symbol K which is described as a function which is then processed in feature space with symbol A which is the academic dimension, s is the social dimension, T the technological dimension, I the individual indicator, E the external factor and T the time. All these symbols will support the multidimensional process of Pro Growth Constructive Interaction and machine learning related to identifying lecturer performance. Next, let's carry out the matrix representation process with the equation s which is represented as a matrix:

$$D = \begin{bmatrix} A_1 & S_1 & T_{e1} & I_1 & E_1 & T_1 \\ A_2 & S_2 & T_{e2} & I_2 & E_2 & T_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_n & S_n & T_{en} & I_n & E_n & T_n \end{bmatrix}. \tag{2}$$

Which will then be processed with a multidimensional tensor by modeling interactions between dimensions which will use tensor symbols, where is the number of individuals, is the dimension, and is the temporal influence which will carry out the process on T_{ijk} with contributions to i towards individuals and j and at time with symbols k. Next, let's process the contribution interaction function constructively on the K symbol which modeled in equation (3):

$$f\left(A,S,T_e,I,E,T\right) = \sum_{i=1}^{n} w_i g_i\left(A,S,T_e,I,E,T\right). \tag{3}$$

Where the symbol is a weight that shows the level of influence of the dimension and the symbol is a non-linear function that will contribute to the academic dimension as in equation (4):

$$_{gA}\left(P,T,R\right) - \ln\left(1+P\right) + \frac{T}{1+e^{-R}}. \tag{4}$$

In equation (4) there a symbol P which is a publication parameter, symbol T is a teaching, and a symbol R is a research parameter. Then there is an optimal performance with symbols (K_{opt}) can be achieved by maximizing the objective function with equation (5):

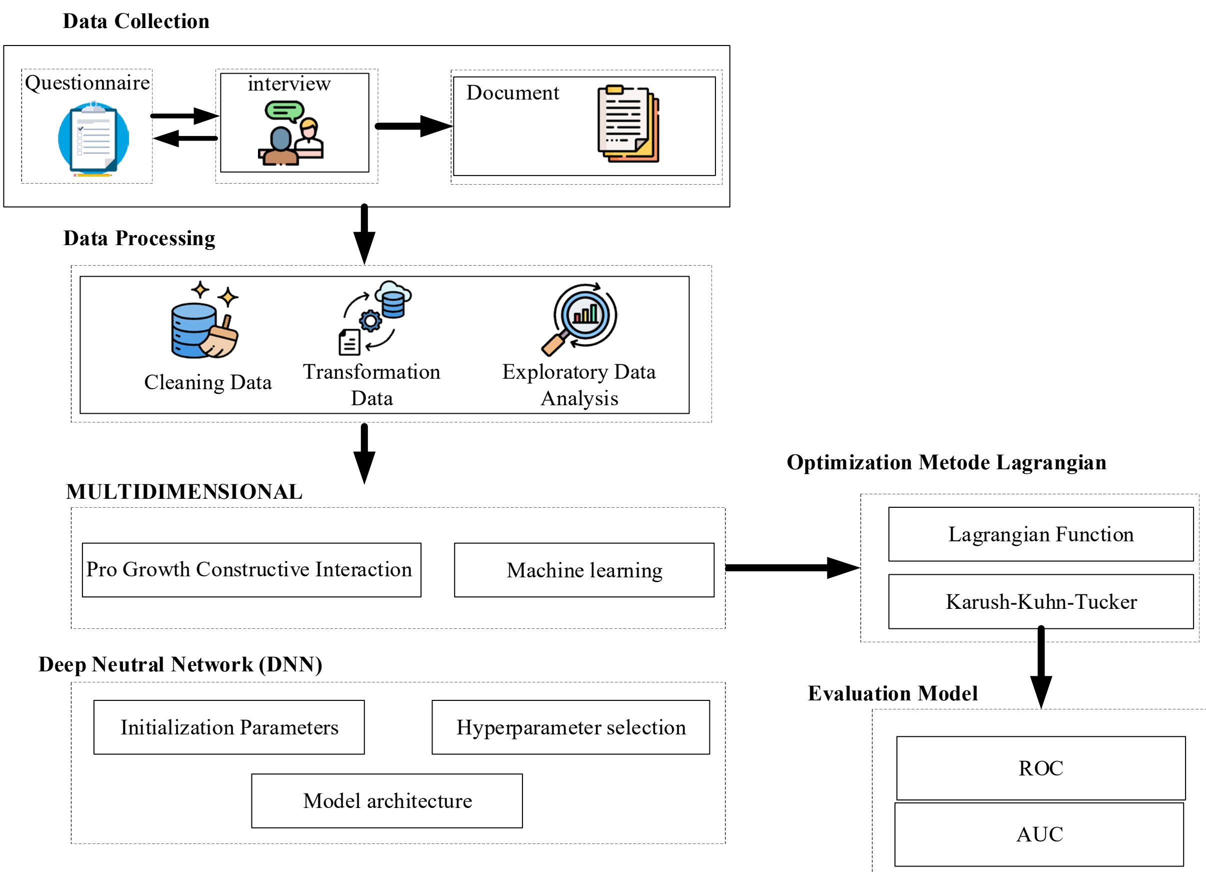

Fig. 1. Architectural framework

$$\max_{w,A,S,T_e,I,E,T} K_i. \quad (5)$$

In equation (5), there restrictions that produce the solution contained in equation (6):

$$w_i \geq 0, \ \sum_{i=1}^{n} w_i = 1,$$

$$0 \leq A, S, T_e I, E, T \leq 1. \quad (6)$$

In equation (6), optimization carried out using the Lagrangian method with the formulation in equation (7):

$$L(K,\lambda) = f(A,S,T_e I,E,T) - \lambda\left(\sum_{i=1}^{n} w_i - 1\right). \quad (7)$$

Which explains that it is a Lagrange multiplicator. After that there is equation (8) which will use a machine learning model for identification and prediction which processes the input data with a matrix symbolized D and value on K_i like:

$$D = \{(A,S,T_e I,E,T)\}, i = 1,2,...,n. \quad (8)$$

In equation (8), the model will use a deep neural network algorithm to process non-linear relationships between dimensions that include symbols θ as a model parameter in equation (9):

$$\hat{K}_i = DNN(A,S,T_e I,E,T;\theta). \quad (9)$$

Then use this algorithm to minimize the loss function to determine the prediction error and complexity of a prediction model that contains the following equation (10):

$$\text{Loss} = \frac{1}{n}\sum_{i=1}^{n}\left(K_i - \hat{K}_i\right)^2 + \lambda\|\theta\|_2^2. \quad (10)$$

$\lambda\|\theta\|_2^2$ is a symbol for regularization to avoid overfitting in deep neural network algorithms. Next, the multidimensional dimensions optimized using the formulation in equation (11):

$$P = w_A A + w_s S + w_T T + w_I I + w_E E + w_\tau \tau. \quad (11)$$

In equation (11), lecturer performance is symbolized by (p) being represented as a linear combination of several multidimensional and academic dimensions symbolized by (A) social (S), technological (T), individual (I), external (E) and temporal (T). Then the machine learning model optimized with the formulation in equation (12):

$$P_{\text{optimized}} = w_A A + w_s S + w_T T + w_I I + w_E E + w_\tau \tau. \quad (12)$$

After equation (12) is processed, there training of a machine learning model with multidimensional dimensions as a target feature on the symbol $P_{optimized}$ with equation (13):

$$P_{ML} = f(A,S,T,I,E,\tau;\theta). \quad (13)$$

In equation (13), the results compared with the final prediction of the symbol P_{ML} with P_{actual} to evaluate performance use values ROC-AUC.

5. Results of multidimensional approach and machine learning-based mathematical models

5. 1. Applying parameters to Pro Growth Constructive Interaction with a multidimensional approach

The Pro Growth Constructive Interaction (PGCI) approach is a strategy to improve lecturer performance through multidimensional-based collaborative interactions that include academic, social, technological, individual, external, and temporal dimensions. The academic dimension focuses on research, teaching, and publication productivity, while the social dimension emphasizes networking to create an inclusive environment. Technology supports digital learning and efficiency, while the individual dimension covers motivation, time management, and life balance. External factors involve industry policies and demands, and the temporal dimension ensures time optimization. Based on this application, there is a mathematical formulation in (14):

$$p_{pred} = w^T \cdot D + f_{ML}(D;\Theta) - \lambda \cdot ||w||^2. \quad (14)$$

Equation (14) will then be implemented in a mathematical model with machine learning to determine and identify lecturer performance predictions. Based on (14), the graph in Fig. 2 below is produced.

Fig. 2 shows that the dimension with the highest average contribution to lecturer performance is the Temporal dimension with an average value of 0.177062. This indicates that the time factor or temporal management has the most significant influence in supporting overall performance. The Technology dimension follows with an average of 0.174122, which indicates that the use of technology is also an important component in supporting performance. The iocial (0.167044) and кxternal (0.165670) dimensions came next, highlighting the importance of social interactions and external influences in supporting performance. Meanwhile, the Individual dimension has an average of 0.163610, indicating a slightly lower contribution than the other dimensions, but still relevant. These findings provide insight that performance improvement strategies can be focused on optimizing dimensions that have high contributions, especially on temporal and technological aspects, without neglecting other dimensions that also make significant contributions. Then there the results of the Application of Pro Growth Constructive Interaction with a Multidimensional Approach in the form of a heatmap visualization contained in the following Fig. 3.

Fig. 3 visualizes the average interactions between dimensions using a heatmap, which provides an intuitive picture of the strength of the relationship between pairs of dimensions. An average interaction matrix is used as the main data, where each element indicates the strength of the relationship between two specific dimensions, such as Academic, Social, or Technology. The results of this analysis can help identify which dimensions have a significant influence on other dimensions, so that it can be the basis for strategies to strengthen interactions between relevant dimensions. After the visualization, there a process of multidimensional machine learning that will identify the performance of lecturers as shown in Fig. 4.

Fig. 4 compares the actual performance with the predicted performance based on the interaction between dimensions, specifically the interaction between technology and social. In Fig. 4, the dots represent actual performance, while the red line shows the performance predicted by the model. The X-axis represents the interaction between the technology and social dimensions, while the Y-axis represents the performance values. If the dots and the red line are close to each other, it indicates that the model successfully predicted the performance accurately. Conversely, a large difference between the points and the line indicates that the model is less precise in predicting performance based on the interaction between dimensions. The results in Fig. 4 able to evaluate the extent to which the model is able to capture the relationship between the analyzed dimensions and actual performance, providing insight into the effectiveness of the model in predicting performance.

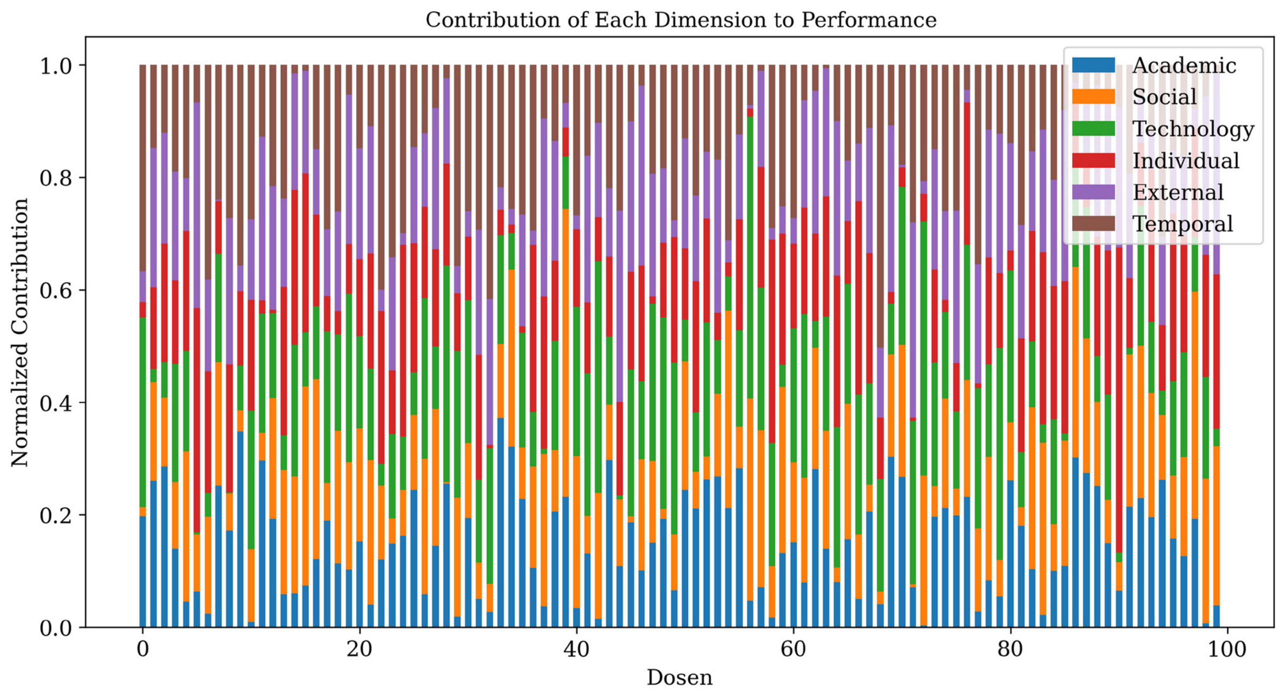

Fig. 2. Dimension contribution graph

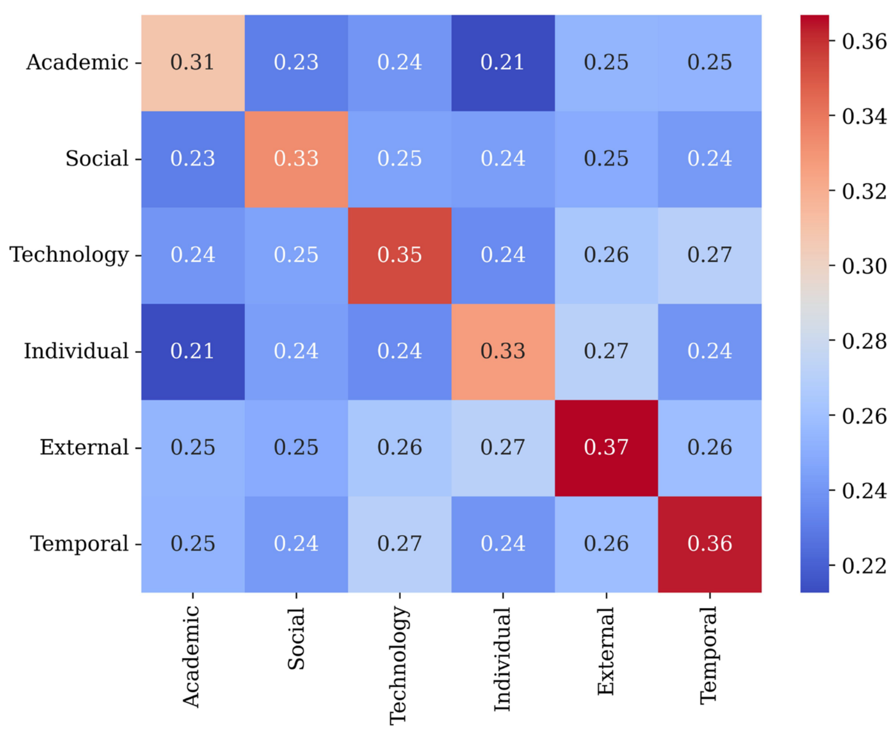

Fig. 3. Heatmap visualization

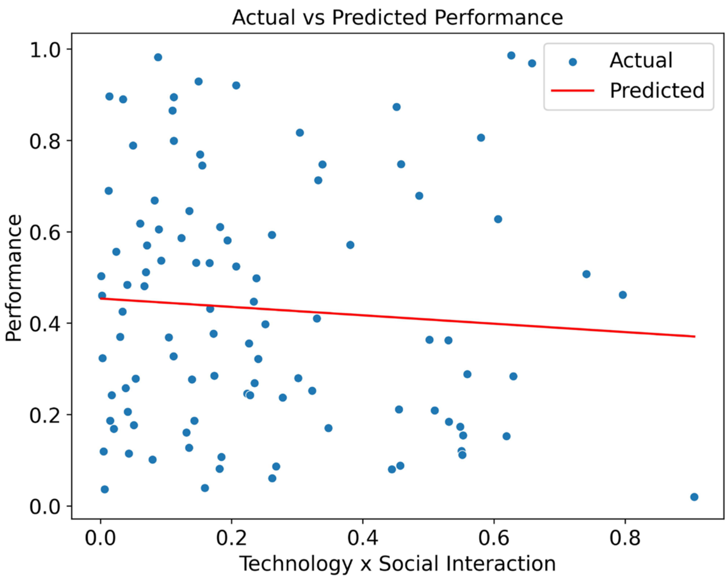

Fig. 4. Prediction chart

5. 2. Implementation of parameters for optimization of mathematical models with machine learning algorithms

Below present the results of the model optimization to identify lecturer performance by calculating the optimized performance obtained through the application of optimized weights on various dimensions that affect lecturer performance. The first process performed is to perform matrix multiplication between lecturer performance data and optimized weights, which results in a more accurate and structured performance value. These results are then entered into a new column in the dataset labeled Optimized_ Performance. There is then a visualization of the weight distribution for each dimension used in the optimization calculation. The bar graph displayed gives a clear picture of how the weights are distributed across the various dimensions, with dimensions that have a greater contribution to lecturer performance receiving higher weights. This graph shows a more balanced weight distribution or focus on factors that are more influential in determining lecturer performance. The following weight optimization graph is found in Fig. 5.

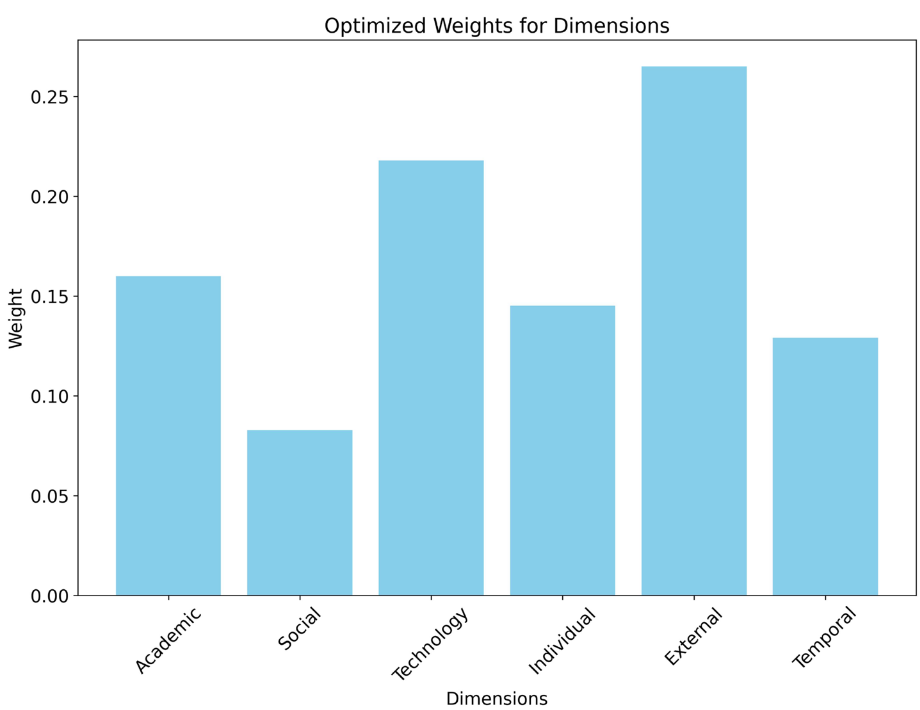

Fig. 5. Weight optimization on each dimension

Then a comparison made between the actual performance and optimized performance. This graph shows how lecturer performance changes after optimization is applied with equations (12), (13), the results obtained by optimized performance tend to show better and structured results. This comparison provides a visual representation of the effectiveness of the optimization. The results of the weight optimization for each dimension are presented to provide deeper insight into the factors that contribute to improving lecturer performance. Each dimension has a different weight, reflecting its contribution to a more optimized performance outcome. With this understanding, lecturer performance development strategies can be more focused on the most influential dimensions. The following is a graph of the comparison before optimization and after optimization using the mathematical model in Fig. 6.

In Fig. 6, the optimization results show a significant increase in lecturer performance, with an average increase of 0.0735 or about 7.35 % after the application of a mathematical model based on machine learning algorithms. This improvement is achieved through adjusting the weights on various dimensions that affect lecturer performance. The dimension with the largest contribution is the external dimension, with a weight of 0.2650, which reflects the importance of institutional support, policies, and access to resources in driving lecturer performance. Next, the technology dimension has a weight of 0.2179, indicating that the application of technological innovations, both in teaching and research, greatly contributes to better achievement. The academic dimension and individual dimension have weights of 0.1600 and 0.1452 respectively, emphasizing the importance of professional achievement and individual quality of lecturers in the performance transformation process. Meanwhile, the temporal dimension with a weight of 0.1291 and the social dimension with a weight of 0.0828 show that time management and social relationships also play a role, although not as big as the other dimensions. These results provide insight that machine learning-based optimization is able to prioritize critical factors, thus supporting more effective strategies in improving overall lecturer performance.

Fig. 6. Comparison before and after optimization

6. Discussion of model predictions in looking at the performance of air transportation vocational education

This research will discuss a multidimensional approach utilizing the Lagrangian method supported by a deep neural network algorithm in identifying and predicting lecturer performance. In the process, the multidimensional approach succeeded in making it easier to identify parameters related to lecturer performance which will then be processed using the Lagrangian method combined with a deep neural network algorithm to produce a model that can identify and predict lecturer performance. Multidimensional will use dimensions such as academic, social, technological, individual, external and temporal which are able to increase understanding of lecturer performance. The results of the model in predicting and identifying lecturer performance are shown in Fig. 4 which carries out a process based on the mathematical formulation of the Lagrangian method and the deep neural network algorithm shown in (2)–(5) where in the process the Lagrangian method needed in the deep architecture. learning so that it will form a model that produces the formulation in (6)–(9). Meanwhile, for (10) it used to see whether the model is experiencing overfitting and for problems (11)–(13) it used for evaluating the model so that the model can work better. This is proven by Fig. 2 which identifies all lecturer performance parameters combined with equation (14). In the research, there are features that provide benefits for identifying lecturer performance transformations involving various parameters that are designed comprehensively. Features include Pro Growth, multidimensional dimensions along with machine learning-based mathematical model features that are capable of processing data predictively, analyzing relationships between parameters, and providing personal recommendations for improving performance. The advantage of this research compared to similar research is that it is a multidimensional approach which includes aspects of pedagogy, research, community service and administration, thus providing a comprehensive picture of lecturer performance.

In Part 2, there are research results related to the application of management parameters and risk analysis in increasing organizational effectiveness. The results obtained in this research by applying multidimensional and machine learning-based mathematical models can overcome limitations in determining parameters and variables for techniques that have been carried out in previous research, especially in terms of determining key variables and structural data processing. Overall, all the results obtained provide evidence that the proposed approach can make a significant contribution in improving employee performance through constructive interactions that support growth.

This is different from what was done by [22] who stated that constructive interactions between leaders and employees have a significant impact on improving performance in the work environment, which then results in interactions that are biased towards open communication and differences in goals so that identification errors and low accuracy often occur. Based on this, machine learning algorithms will be utilized to avoid biased information due to open interactions in the system. This research will use a multidimensional approach, namely pedagogy, research, community service, and administration and this research offers analysis based on mathematical models and machine learning, which allows accurate performance predictions and provides personalized recommendations. which can be tailored to the lecturer's individual needs.

The limitations of this research lie in the machine learning-based mathematical model which really needs good quality data so that predictions can be valid. If the data quality is incomplete, it will lead to biased predictions and the limitations of this research lie in its multidimensionality which requires conformity to parameters. Meanwhile, the weakness of this research lies in its dependence on adequate technological infrastructure, such as strong hardware and the latest software. This research can be developed by expanding the scope of data from various types of educational institutions to increase the generalization of the model. Then it can be developed using the integration of IoT technology or a cloud system to enable real-time collection of lecturer performance data, providing more responsive recommendations. The addition of explainable AI (XAI) features can also make it easier to understand analysis results, increasing adoption and acceptance by non-technical users.

7. Conclusions

1. This study shows that the multidimensional approach based on the Lagrangian method and deep neural network algorithm is effective in identifying and predicting lecturer performance with high accuracy reaching 92.4 %. Temporal and technological dimensions contribute significantly to lecturer performance, while the external dimension is the main factor with the highest weight in performance optimization. The optimization process managed to improve the average performance by 7.35 %, providing evidence that the developed model has high validity in supporting data-based decision making.

2. Modeling using tensor representations and data visualizations, such as heatmaps and prediction graphs, provide deep insights into the interactions between dimensions that affect lecturer performance. The results of weight distribution optimization between dimensions show the external and technology dimensions as strategic priorities in performance development. Thus, this machine learning-based mathematical model can be a useful tool to evaluate and improve performance in higher education institutions more broadly.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The study was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

References

1. Weng, A. K.-W., Chang, H.-Y., Lai, K.-K., Lin, Y.-B. (2024). Topic Modeling on Peer Interaction in Online and Mobile Learning of Higher Education: 1993–2022. Education Sciences, 14 (8), 867. https://doi.org/10.3390/educsci14080867
2. Chu, W., Liu, H., Fang, F. (2021). A Tale of Three Excellent Chinese EFL Teachers: Unpacking Teacher Professional Qualities for Their Sustainable Career Trajectories from an Ecological Perspective. Sustainability, 13 (12), 6721. https://doi.org/10.3390/su13126721
3. Nam, P. S., Tuong, H. A., Weinhandl, R., Lavicza, Z. (2022). Mathematics Teachers' Professional Competence Component Model and Practices in Teaching the Linear Functional Concept – An Experimental Study. Mathematics, 10 (21), 4007. https://doi.org/10.3390/math10214007
4. Suh, J., Matson, K., Seshaiyer, P., Jamieson, S., Tate, H. (2021). Mathematical Modeling as a Catalyst for Equitable Mathematics Instruction: Preparing Teachers and Young Learners with 21st Century Skills. Mathematics, 9 (2), 162. https://doi.org/10.3390/math9020162
5. Ponce-Jara, M. A., Ruiz, E., Gil, R., Sancristóbal, E., Pérez-Molina, C., Castro, M. (2017). Smart Grid: Assessment of the past and present in developed and developing countries. Energy Strategy Reviews, 18, 38–52. https://doi.org/10.1016/j.esr.2017.09.011
6. Manzhos, S., Ihara, M. (2022). Advanced Machine Learning Methods for Learning from Sparse Data in High-Dimensional Spaces: A Perspective on Uses in the Upstream of Development of Novel Energy Technologies. Physchem, 2 (2), 72–95. https://doi.org/10.20944/preprints202203.0007.v1
7. Mystakidis, S., Berki, E., Valtanen, J.-P. (2021). Deep and Meaningful E-Learning with Social Virtual Reality Environments in Higher Education: A Systematic Literature Review. Applied Sciences, 11 (5), 2412. https://doi.org/10.3390/app11052412
8. Tang, J., Zhou, X., Wan, X., Daley, M., Bai, Z. (2022). ML4STEM Professional Development Program: Enriching K-12 STEM Teaching with Machine Learning. International Journal of Artificial Intelligence in Education, 33 (1), 185–224. https://doi.org/10.1007/s40593-022-00292-4
9. Kyriakides, L., Creemers, B. P. M., Antoniou, P. (2009). Teacher behaviour and student outcomes: Suggestions for research on teacher training and professional development. Teaching and Teacher Education, 25 (1), 12–23. https://doi.org/10.1016/j.tate.2008.06.001
10. Antoni, A., Arfah, M., Fachrizal, F., Nugroho, O. (2024). Developing a model of association rules with machine learning in determining user habits on social media. Eastern-European Journal of Enterprise Technologies, 3 (2 (129)), 55–61. https://doi.org/10.15587/1729-4061.2024.305116
11. Rahmatika, A., Al-khowarizmi, A., Akrim, A., Nugroho, O., Anu, T. A. (2024). Using relational learning in exploring the effectiveness of using hashtags in future topics and user relations in X. Eastern-European Journal of Enterprise Technologies, 3 (2 (129)), 62–68. https://doi.org/10.15587/1729-4061.2024.306726

12. Liu, H., Ding, J., Yang, L. T., Guo, Y., Wang, X., Deng, A. (2020). Multi-Dimensional Correlative Recommendation and Adaptive Clustering via Incremental Tensor Decomposition for Sustainable Smart Education. IEEE Transactions on Sustainable Computing, 5 (3), 389–402. https://doi.org/10.1109/tsusc.2019.2954456
13. Yanes, N., Mostafa, A. M., Ezz, M., Almuayqil, S. N. (2020). A Machine Learning-Based Recommender System for Improving Students Learning Experiences. IEEE Access, 8, 201218–201235. https://doi.org/10.1109/access.2020.3036336
14. Mahmud, M., Kaiser, M. S., Hussain, A., Vassanelli, S. (2018). Applications of Deep Learning and Reinforcement Learning to Biological Data. IEEE Transactions on Neural Networks and Learning Systems, 29 (6), 2063–2079. https://doi.org/10.1109/tnnls.2018.2790388
15. Jdid, B., Hassan, K., Dayoub, I., Lim, W. H., Mokayef, M. (2021). Machine Learning Based Automatic Modulation Recognition for Wireless Communications: A Comprehensive Survey. IEEE Access, 9, 57851–57873. https://doi.org/10.1109/access.2021.3071801
16. Kim, J. (2023). Leading teachers' perspective on teacher-AI collaboration in education. Education and Information Technologies, 29 (7), 8693–8724. https://doi.org/10.1007/s10639-023-12109-5
17. Wang, Z. A. (2024). Physical Education Teaching Quality Assessment Model Based on Gaussian Process Machine Learning Algorithm. International Journal of Maritime Engineering, 1 (1). https://doi.org/10.5750/ijme.v1i1.1399
18. Phillips, P. A., Wright, C. (2009). E-business's impact on organizational flexibility. Journal of Business Research, 62 (11), 1071–1080. https://doi.org/10.1016/j.jbusres.2008.09.014
19. Arnold, V., Benford, T., Canada, J., Sutton, S. G. (2011). The role of strategic enterprise risk management and organizational flexibility in easing new regulatory compliance. International Journal of Accounting Information Systems, 12 (3), 171–188. https://doi.org/10.1016/j.accinf.2011.02.002
20. Okorie, O., Subramoniam, R., Charnley, F., Patsavellas, J., Widdifield, D., Salonitis, K. (2020). Manufacturing in the Time of COVID-19: An Assessment of Barriers and Enablers. IEEE Engineering Management Review, 48 (3), 167–175. https://doi.org/10.1109/emr.2020.3012112
21. Shukla, S. K., Sushil, Sharma, M. K. (2019). Managerial Paradox Toward Flexibility: Emergent Views Using Thematic Analysis of Literature. Global Journal of Flexible Systems Management, 20 (4), 349–370. https://doi.org/10.1007/s40171-019-00220-x
22. Leelaluk, S., Minematsu, T., Taniguchi, Y., Okubo, F., Shimada, A. (2022). Predicting student performance based on Lecture Materials data using Neural Network Models. Proceedings of the 4th Workshop on Predicting Performance Based on the Analysis of Reading Behavior - DC in LAK22 co-located with 12th International Learning Analytics and Knowledge Conference (LAK22), 11–20. Available at: https://ceur-ws.org/Vol-3120/paper2.pdf
23. Kang, W. (2021). Explaining Effects of Transformational Leadership on Teachers' Cooperative Professional Development through Structural Equation Model and Phantom Model Approach. Sustainability, 13 (19), 10888. https://doi.org/10.3390/su131910888
24. Goga, M., Kuyoro, S., Goga, N. (2015). A Recommender for Improving the Student Academic Performance. Procedia - Social and Behavioral Sciences, 180, 1481–1488. https://doi.org/10.1016/j.sbspro.2015.02.296
25. Suyatmo, S., Ekohariadi, E., Wardhono, A. (2024). Identify Factors That Influence Hard Skill Competency and Soft Skill Competency Through the Quality of Teaching in Aviation Vocational Education. IJORER : International Journal of Recent Educational Research, 5 (3), 599–611. https://doi.org/10.46245/ijorer.v5i3.584
26. Cao, B., Hassan, N. C., Omar, M. K. (2024). The Impact of Social Support on Burnout among Lecturers: A Systematic Literature Review. Behavioral Sciences, 14 (8), 727. https://doi.org/10.3390/bs14080727