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RESEARCH ARTICLE

Leveraging AI in Product Management for the Digital Transformation of Higher Education

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***Abstract*—Artificial Intelligence (AI) is increasingly transforming higher education by enabling data-driven product management, intelligent decision-making, process automation, and adaptive institutional services. Artificial Intelligence (AI) is transforming higher education from data to decisions, automation to personalization, and services to learning. While organizational influence and AI's predictive power are vital in the process of achieving digital transformation, it is important to understand their significance. The present study is aimed at studying the applications of AI in higher education for product management through the multidimensional approach and machine learning techniques. Partial Least Squares Structural Equation Modeling (PLS-SEM) is used to analyze the relationships between AI-enabled product management capabilities and digital transformation outcomes, while machine learning is used to analyze the institutional transformation patterns and predictive performance. AI product strategy, decision quality, institutional agility, digital governance, and digital transformation are closely interconnected areas, as revealed by the structural analysis, where the organizational capacities related to AI products are crucial for institutional transformation. The overall classification accuracy of the machine learning assessment is 97.5%, and in the categories of institutional transformation, the precision, recall, and F1 scores are all of good predictive performance. Experimental analysis results are also presented by the connection between the features of the institution, the learning behavior, and the confusion matrix to estimate the reliability of the model and the capability of the model to predict the learning behavior. The findings suggest that a combination of explanatory structural modeling and predictive machine learning has the potential to be a comprehensive solution to the challenge of evaluating the transformation of higher education brought about by AI. The recommended approach provides practical recommendations for academic administration, technology leaders, and product managers to enhance institutional decision-making, resource utilization, digital maturity, and approaches to AI transformation.**

Keywords—Artificial Intelligence, Product Management, Digital Transformation, Higher Education, Machine Learning, PLS-SEM, Decision Support Systems, Institutional Digital Transformation.

I. Introduction

Artificial Intelligence has emerged as a game-changer in the realm of digital transformation, reshaping the way organizations process information, automate processes, assist in decision-making, and adapt to the evolving needs of stakeholders. In the higher education sector, the use of technologies like machine learning (ML), natural language processing (NLP), predictive analytics, and intelligent automation is starting to pervade the academic and administrative settings [1].

Through that, institutions can enhance their digital services, use these services to the best of their resources, learn about the behavior of stakeholders, and help in the process of evidence-based decision-making [2]. AI is becoming a crucial part of universities' transformation plans as they are increasingly expected to provide personalized, efficient, and technology-driven services. The growing need for customized, efficient, and technologically enabled services has opened the doors to the growing use of AI in institutional transformation strategies [3]. Product management plays a key role in this context, connecting technological features with the needs of the students, faculty, administration, and the stakeholders. AI-powered product management can help with data-driven analysis, enhance decision-making processes, automate operational tasks, analyze user feedback, and facilitate ongoing institutional digital product and service improvement [4]. So, it is not enough to just deploy AI technologies to attain digital transformation. The successful implementation of such capabilities within the frame of organizational decision making and product-management processes is also crucial [5].

While extensive research has been undertaken on the application of AI in higher education, the majority of studies have been dedicated to personalized learning, intelligent tutoring, automated assessment, student performance, and so on. There is significantly less research that has addressed the evaluation of AI-based product management from explanatory and predictive perspectives [6]. A sense of relationships between the capabilities of organizational AI is crucial, but predictive modeling can also uncover intricate patterns related to institutional transformation results.

To address the gap, this paper proposes a combination of a partial least squares structural equation modeling (PLS-SEM) and machine learning approach. This investigation is based on the data that was gathered from 384 students in higher education institutions in Chicago, USA. AI capability and digital transformation can be analyzed in terms of their structural relationship by PLS-SEM, and the pattern of institutional transformation can be predicted by machine learning. This holistic perspective aims to provide actionable recommendations for higher education leaders and technology managers for making decisions on AI investments, products, institutional decision-making, and sustainable digital transformation.

II. Related works

In recent years, the power of AI has been expanding its reach and influence in the realm of digital transformation in higher education, significantly. AI technologies have been utilized in different ways and on different topics in the context of personalized learning, including personalized learning, AI tutors, automated assessment, predictive analytics, support for students, interaction with learners, etc. Such characteristics allow HEIs to identify complex education data, analyze the patterns of behaviors, enhance services and service delivery, and create learning environments that respond to behaviors. Research on digital transformation also highlights the role and importance of the institutional strategies, technological infrastructure, the readiness of the organization, and the participation of the stakeholders in delivering the technology successfully [9].

Other education use cases are available, too: AI-driven analysis and intelligent automation have also proven to be beneficial in the optimization of resources, streamlining of workflows, and strategic planning in education organizations [10]. AI applications are also becoming a common part of product management, such as customizing user experiences, gaining predictive insights, analyzing user feedback, developing new products, and automating product processes [11]. Such features can support product managers' decision-making and continuous improvement of digital products to keep them relevant to stakeholders' needs [12].

But most of the recent research concentrates on the application of AI in the educational field, the digital transformation, and product management [13]. Very little research on using AI for product management has been done that combines explanatory structural analysis and machine learning-based predictive evaluation [14]. To achieve such an overview of the organizational relationship and the predictive relationships of digitalization in higher education, PLS-SEM can be combined with machine learning [15].

III. Proposed framework

The framework proposed here offers an integrated analytical perspective on the role of AI for product management and digital transformation in higher education. It combines the power of artificial intelligence with predictive intelligence, the organizational transformation factors, and the explanatory structural modeling. The main dimensions of organizational structure measured are AI product strategy, decision quality, institutional agility, digital governance, and digital transformation.

The explanatory layer is designed to explain the connections between institutional constructs and the effect of AI-powered capabilities on digital transformation through the lens of PLS-SEM. This layer enables a systematic examination of relationships between strategic AI adoption, decision-making processes, institutional agility, governance, and transformation results. It thus provides a useful framework for thinking about the organization of AI-driven transformation as well as the adoption of technology. The overall structure of the proposed framework, including data preprocessing, explanatory analysis with PLS-SEM, predictive modeling with machine learning, and institutional transformation assessment, can be seen in Fig. 1.

Fig. 1. Overall System Architecture of the Proposed AI-Enabled Product Management Framework

The prediction layer is supported by structural analysis carried out by applying the institutional transformation assessment and machine learning approach. It is a reflection of multivariate patterns associated with different maturity levels of digital and is moving from relationship analysis to predictive intelligence. These analysis methods enable the interpretation of structural and predictive evidence in the same institutional environment.

The magic of the framework lies in the ability to establish a link between the use of AI-based product management and explanatory and predictive analytics in higher education. This holistic perspective helps institutional leaders master the most important drivers for change, benchmark their digital readiness, inform strategic choices, increase digital governance, and commit resources to transformative AI investments for institutional change.

IV. METHODOLOGY

The study uses a quantitative analytical approach combining the Partial Least Squares Structural Equation Modeling (PLS-SEM) methodology and machine learning to examine the effectiveness of AI-based product management and digital transformation in higher education. The methodology integrates explanatory structural analysis and modeling with predictive modeling, allowing for systematic evaluation of organizational relationships, institutional features, and outcomes of digital transformation. The methodological process of the proposed framework is presented in Fig. 2, which includes sequential data preparation, parallel PLS-SEM and machine-learning analysis procedures, integrated performance evaluation, and institutional transformation assessment procedures.

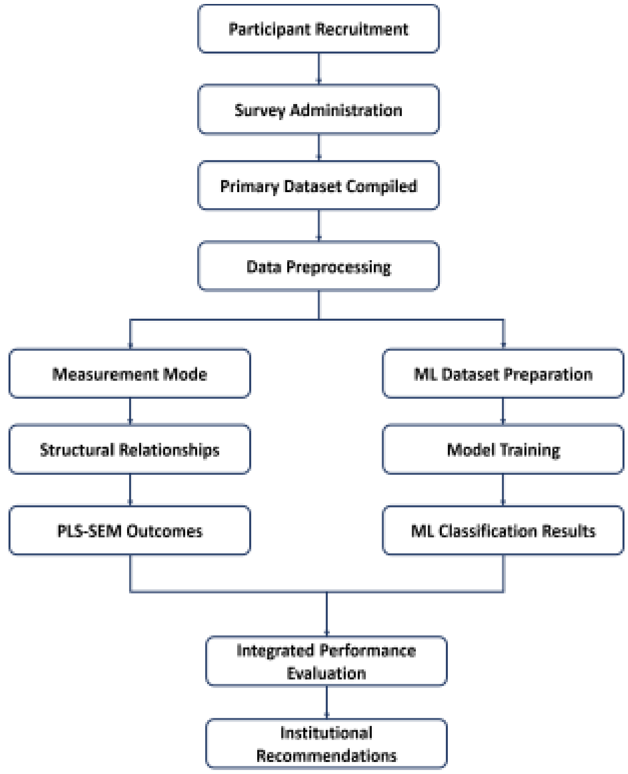

Fig. 2. Workflow of the Proposed PLS-SEM and Machine-Learning Methodology

The methodology starts with data collection and data preprocessing, followed by feature and construct organization for the two analytical pathways. The PLS-SEM pathway is used for measurement model validation and structural relationship evaluation, and the machine-learning pathway is used for MLP-based predictive modeling for categorizing institutional transformation conditions. Finally, the results of both streams are combined and used to offer complementary explanations and predictions for institutional digital transformation.

A. Dataset and Data Collection

Two complementary datasets were used for the structural and predictive analysis. The first data set is primary data gathered by the survey from 384 respondents at higher education institutions in Chicago, United States. The respondents are students, faculty, administrative staff, and institutional stakeholders from the digital services. The data was collected with a structured questionnaire with a 5-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. The convenience sampling approach was used to recruit and get responses from the people who are directly exposed to the services that are enabled with AI and those who are part of digital transformation projects. This survey data is mainly used for measurement and structural model evaluation using PLS-

SEM. 4,800 institutional observations, covering strategic, operational, technological, and governance aspects, are grouped into four categories of digital transformation for machine learning-based predictive analysis. Of the latter, 960 observations are used for final evaluation and the rest for developing and validating the model.

B. Data Preprocessing and Feature Organization

All the data collected is prepared systematically in advance of the analytical modeling. The survey answers are checked for consistency, suitability of answers, missing observations, and completeness of answers. The responses given in the questionnaires are quantitatively coded based on their Likert scale ratings and categorized under their respective constructs and analysis features. The preprocessing phase sets up a uniform representation of the data from institutions for statistical and predictive analysis. AI-related, organizational, operational, and transformation attributes relevant to the assessment are grouped to better facilitate construct-level assessment for PLS-SEM and feature-level assessment for machine learning. Both methods can analyze various components of the same institutional transformation context based on this widely shared analytical basis.

C. PLS-SEM Measurement Model

The study conducted is empirical, with data gathered from primary sources of 384 respondents from higher institutions of learning in Chicago, Illinois, United States. The respondents are students, faculty, administrative staff, and other stakeholders related to institutional digital services. Structured questionnaires with a 5-point Likert scale (1-Strongly Disagree to 5-Strongly Agree) were used to collect data. The sample was convenient, and participants with relevant experience in AI-facilitated institutional services and digital transformation projects were selected.

Measuring the validity of measurement models and structural relationships based on the survey data was done using PLS-SEM. The measurement model tests the relationship between the observed indicators of the questionnaires and their underlying latent constructs. First, the reliability and validity of the measurement structure are tested by analyzing indicator reliability, internal consistency, composite reliability, convergent validity, and discriminant validity; then, the relationships between the institutional constructs are analyzed.

D. Structural Model Assessment

After measurement-model validation, the structural model is then evaluated to check the relationships between AI-enabled institutional capabilities and digital transformation. Based on the magnitude and direction of the estimated path coefficients, it evaluates the relative contribution of the AI product strategy, decision quality, institutional agility, digital governance, and related organizational factors on transformation outcomes. Another measure used to assess the R^2 of variance accounted for by the structural predictors is the coefficient of determination. This assessment offers an explanatory view of the relationship between AI-supported product-management functions and organizational traits and the phenomenon of digital transformation in higher education institutions.

E. Machine-Learning Predictive Modeling

The predictive assessment of institutional digital transformation is based on a multilayer perceptron (MLP) neural network integrated with the machine learning component. Observations are classified in four transformation categories: "High Digital Maturity," "Moderate Transformation," "Early Adoption Stage," and "Legacy Operational Risk" based on institutional, technological, strategic, operational, and governance features. The data set includes 4800 data points, with 960 points held back for testing. The MLP is trained for 60 epochs, and the learning rate is decreased gradually to ensure stable convergence. The training score and cross-validation score are monitored to measure generalization. The accuracy, precision, recall, F1-score, confusion-matrix analysis, and learning-curve analysis are used to predict the performance.

F. Institutional Digital Transformation Assessment

The predictive analysis investigates the patterns of institutional transformation found in the experimental data. The resulting predictions give a data-driven evaluation of the conditions for digital transformation and supplement the explanatory evidence that is formed by PLS-SEM. The combination of the two analytical methods offers two unique but complementary points of view. PLS-SEM can detect statistical significance in the structural relationships among organizational constructs, while machine learning can identify nonlinear and multivariate patterns of institutional transformation outcomes. The joint analysis can then give a more comprehensive picture of AI product management than either of the analytical methods alone.

G. Performance Evaluation

Indicator reliability, internal consistency, composite reliability, convergent validity, discriminant validity, structural path significance, and explanatory power are used for the PLS-SEM component evaluation. They confirm the reliability of the measurement structure and the statistical significance of the relationships in the structural model. The performance of machine learning is assessed by classification accuracy, precision, recall, F1 score, and confusion matrix analysis. Training and validation behavior is also analyzed using learning-curve analysis to gain understanding of the convergence and generalization properties. Relationships and institutional characteristics are also explored in detail to aid the interpretation of the predictions.

H. Mathematical Formulation

The analytical framework integrates structural relationship assessment with machine-learning-based predictive evaluation. The principal mathematical formulations are presented below.

The structural relationship between AI-enabled institutional capabilities and digital transformation is represented as

$$DT = \beta_1 APS + \beta_2 DQ + \beta_3 IA + \beta_4 DG + \varepsilon \quad (1)$$

where DT represents Digital Transformation, APS denotes AI Product Strategy, DQ represents Decision Quality, IA denotes Institutional Agility, DG represents Digital Governance, β_1 to β_4 denote the corresponding structural coefficients, and ε represents the residual component.

The convergent validity of each latent construct is assessed using Average Variance Extracted,

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{n} \quad (2)$$

Where λ_i represents the standardized factor loading of the i^{th} measurement indicator and n represents the total number of indicators associated with the construct. A higher AVE indicates that the construct explains a greater proportion of variance in its indicators.

The predictive component represents institutional digital transformation as a learned function of the input feature vector,

$$\hat{Y} = f(X; \theta) \quad (3)$$

where $X = [x_1, x_2, \ldots, x_m]$ represents the set of AI-related, organizational, and institutional features, $f(\cdot)$ denotes the machine-learning prediction function, θ represents the learned model parameters, and $\hat{Y}$ denotes the predicted institutional transformation outcome.

The overall predictive performance of the machine-learning model is evaluated using classification accuracy:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

where TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

V. RESULT AND DISCUSSION

The experimental results are assessed in the structural and predictive aspects of the proposed framework. In this study, the PLS-SEM analysis is used to evaluate the indicators' reliability, construct reliability, convergent validity, discriminant validity, and structural relations between the institutional factors. The machine-learning analysis also analyzes digital transformation patterns based on feature relationships, maturity-stage classification, learning behavior, and predictive performance. The findings collectively contribute to a comprehensive picture about the impact of AI-powered product management capabilities and the success of predictive modeling in measuring DT in HEIs.

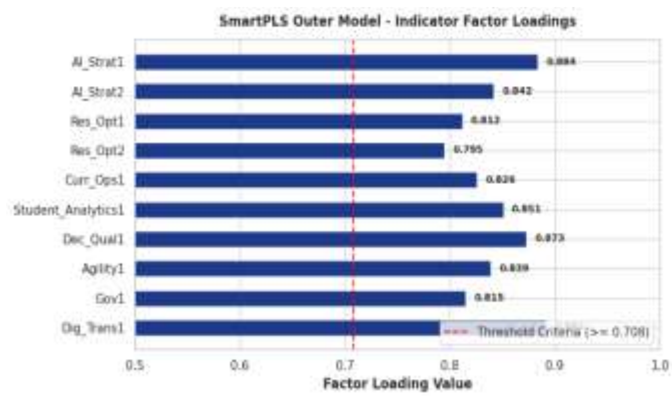

Fig. 3. SmartPLS Outer Model Indicator Factor Loadings

The results of indicator factor loadings in Fig. 3 show that all indicators are beyond the recommended value of 0.708 and range from 0.795 to 0.892. There are significant loadings in areas of AI strategy, resource optimization, curriculum operations, student analytics, decision quality, institutional agility, governance, and digital transformation indicators. The results showed appropriate reliability of the indicators and confirmed that the measurement items were representative of the structural models that were measured.

Fig. 4. Construct Reliability and Convergent Validity Assessment

Fig .4 shows the reliability and convergent validity results. The Cronbach's alpha values range from 0.819 to 0.888, and composite reliability values range from 0.880 to 0.923, which are all higher than the recommended value of 0.70. The range of AVEs is still in the 0.648-0.750 range, much higher than 0.50. Thereby, the results confirm high internal consistency, as well as high construct reliability and good convergent validity for all assessed constructs.

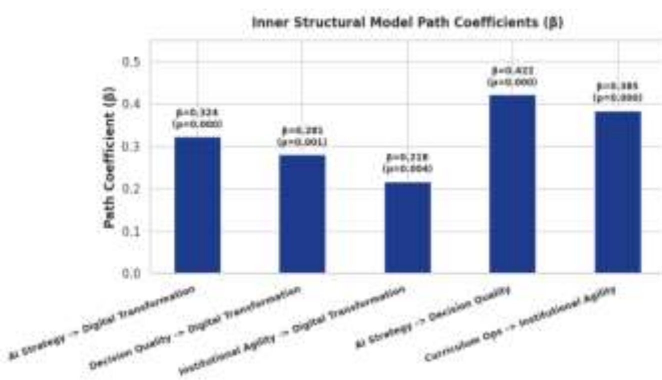

Fig. 5. Structural Model Path Coefficients

The structural relationships among the constructs investigated are shown in Fig. 5. The results show that AI strategy has a positive effect on digital transformation, with the coefficient of $\beta = 0.324$; decision quality has a positive effect, $\beta = 0.281$; and institutional agility has a positive effect, $\beta = 0.218$. AI strategy is related to decision quality at a higher value of $\beta = 0.422$; however, curriculum operations are more related to institutional agility at a value of $\beta = 0.385$. The observed path coefficients are varying contributions of organizational capabilities to digital transformation.

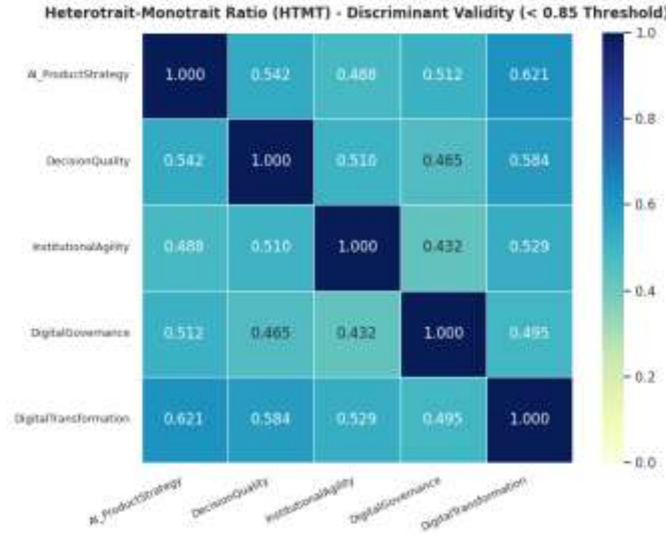

Fig. 6. HTMT-Based Discriminant Validity Assessment

The HTMT matrix in Fig. 6 is used to assess the discriminant validity across the various constructs. Inter-construct values are between 0.432 and 0.621 (still within the threshold of 0.85). The strongest correlation is between AI product strategy and digital transformation with a coefficient of 0.621. The results confirm sufficient empirical separation between the AI product strategy, decision quality, institutional agility, digital governance, and digital transformation in the proposed structural measurement framework.

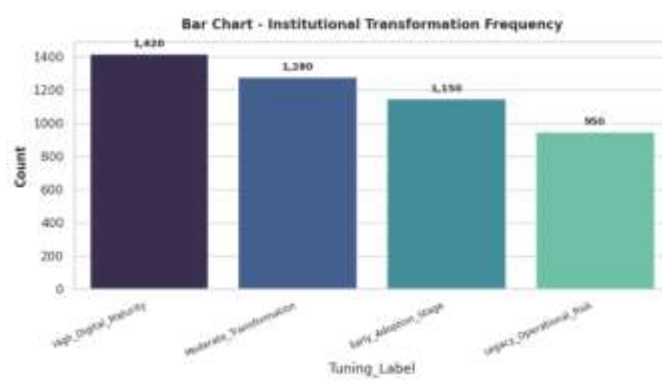

Fig. 7. Distribution of Institutional Digital Transformation Stages

The frequencies of institutional transformation for the four maturity categories are shown in Fig. 7. The highest scores are for High Digital Maturity (1,420 observations), followed by Moderate Transformation (1,280 observations), Early Adoption Stage (1,150 observations), and Legacy Operational Risk (950). The distribution reflects institutions at different stages of digital development and offers a diverse categorical analysis on which to examine transformation characteristics and evaluate predictive performance in varying institutional digital maturity conditions.

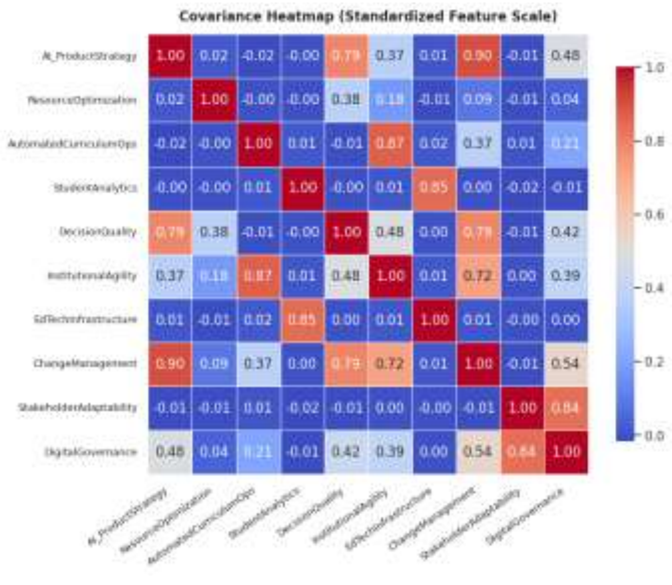

Fig. 8. Covariance Analysis of Institutional Transformation Features

A few institutional properties are found to be correlated with each other in a positive manner, as can be seen in Fig. 8. AI product strategy and AI change management have a correlation of 0.90, and automated curriculum operations and institutional agility have a correlation of 0.87. The next highest scores are for Student Analytics and EdTech Infrastructure (0.85), with Stakeholder Adaptability and Digital Governance coming in at 0.84. As shown, there are strong interdependencies between strategic, technological, operational, and governance aspects of institutional digital transformation.

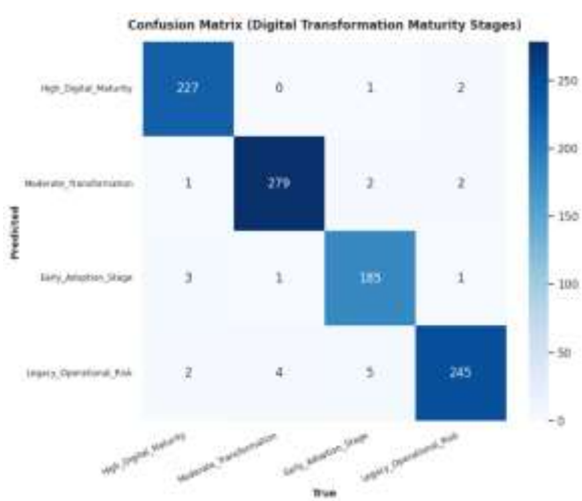

Fig. 9. Confusion Matrix for Digital Transformation Maturity Classification

The confusion matrix in Fig. 9 summarizes the classification results in the four categories of transformation. The model accurately classifies 227 high digital maturity, 279 moderate transformation, 185 early adoption stage, and 245 legacy operational risk instances. The pattern is relatively small for misclassification in all categories, and a strong diagonal pattern is observed. This result shows that the predictive model can successfully classify the different types of digital transformation maturity conditions of institutions with very few misclassifications.

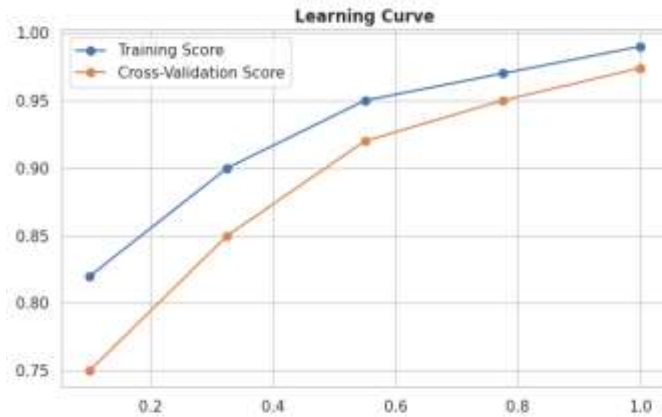

Fig. 10. Training and Cross-Validation Learning Curve

Model learning behavior is shown in Fig. 10, where the learning score gradually improves from about 0.82 to 0.99 and the cross-validation score gradually improves from about 0.75 to 0.97. The difference between the two curves slowly narrows down with the increasing size of the training set, thus highlighting good generalization. Convergence at high scores indicates that they learn in a stable manner, and this convergence indicates that there is not a significant difference between the model's performance on the training set and the validation set.

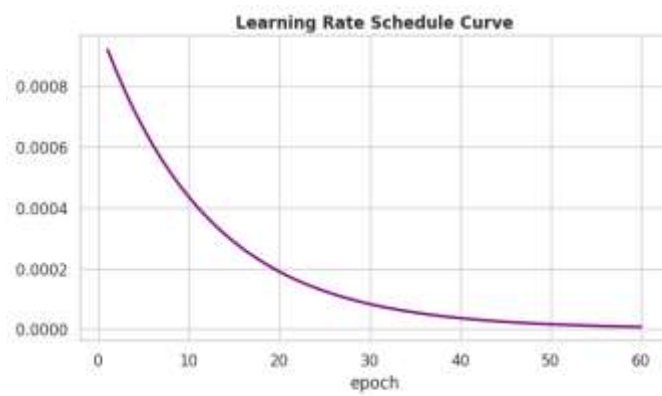

Fig. 11. Learning Rate Schedule During Model Training

The optimization behavior during the model training process is shown in Fig. 11. The learning rate gradually decreases over 60 epochs with the initial value of almost 0.0009 and gradually decreases toward the end of training. A bigger update size helps learn quickly at the early stage of optimization, and a smaller update size helps fine-tune the parameters during the later stage of optimization. This controlled decay helps to ensure stable convergence and to prevent excessive fluctuations of the parameters if the predictive model approaches the optimum solution.

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CLASSIFICATION REPORT:

Target Construct: Digital Transformation of Higher Education
PLS-SEM Explanatory Power (R²): 0.252 (25.2%) | Adjusted R²: 0.244
Model Predictive Accuracy: 97.39999999999999%

                             precision    recall  f1-score   support

     High_Digital_Maturity      0.9742    0.9870    0.9806       230
  Moderate_Transformation      0.9824    0.9824    0.9824       284
      Early_Adoption_Stage      0.9585    0.9737    0.9661       190
  Legacy_Operational_Risk      0.9800    0.9570    0.9684       256

                  accuracy                          0.9750       960
                 macro avg      0.9738    0.9750    0.9743       960
              weighted avg      0.9751    0.9750    0.9750       960
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Fig. 12. Classification Performance of the Digital Transformation Prediction Model

The detailed predictive performance is shown in Fig. 12, showing a total classification accuracy of 97.5% over 960 observations tested. Class-specific precision ranges from 95.85% to 98.24%, recall from 95.70% to 98.70%, and F1-score from 96.61% to 98.24%. In the weighted F1-score, the prediction performance is uniformly good, with an F1 score of 97.50%. The integrated analysis offers complementary explanations and predictions on institutional digital transformation. The PLS-SEM model achieves an R^2 of 0.252, which signifies that observed variance in the digital transformation can be explained by the investigated constructs within the organization with the help of artificial intelligence. This level of explanatory power indicates that AI product strategy, decision quality, institutional agility, and digital governance all have significant explanatory power in terms of the outcomes of institutional transformation, and further organizational, technological, financial, and contextual factors could be important to the explanation of institutional digital transformation. The machine-learning model, on the other hand, is able to classify the digital transformation maturity categories with 97.5% accuracy. These measures have various analytical goals and cannot be directly compared because R^2 describes the variance accounted for in the structural model, while accuracy of classification describes the level of discrimination across categorical outcomes. The results, hence, illustrate the complementary nature of structural explanation and machine learning-based prediction in the proposed framework.

VI. CONCLUSION

This study introduced an integrated model for analyzing the use of artificial intelligence as a tool for product management and its role in digital transformation in higher education. This study offers complementary explanatory and predictive insights into institutional transformation by using PLS-SEM, which is supported by a machine learning-based predictive analysis. The results of the measurement model showed good indicator reliability, internal consistency, and convergent and discriminant validity, indicating a robust validity of the measured constructs. The analysis of the structure further showed that the following significant relationships exist: AI product strategy – decision quality, institutional agility – digital governance, and digital governance – digital transformation. The machine-learning analysis clearly exhibited high power to discriminate between the institutional digital maturity stages, with an overall classification success rate of 97.5% and with high precision, recall, and F1-scores in every transformation category. The learning and validation behavior also showed stable predictive behavior and good generalization. In general, the results show that using AI-driven product management alongside structural and predictive analytics can boost institutional decision-making, transformation evaluation, and strategic planning. The proposed framework offers a data-driven base for higher education institutions looking to improve their digital maturity, organization, and technology-driven operations. The framework could be expanded in the future with the use of larger multi-institutional datasets, a longitudinal study, and validation across different geographic contexts in higher education.

REFERENCES

[1] Benavides, Lina María Castro, Johnny Alexander Tamayo Arias, Martín Darío Arango Serna, John William Branch Bedoya, and Daniel Burgos. "Digital transformation in higher education institutions: A systematic literature review." *Sensors* 20, no. 11 (2020): 3291.

[2] Seo, Kyoungwon, Joice Tang, Ido Roll, Sidney Fels, and Dongwook Yoon. "The impact of artificial intelligence on learner–instructor interaction in online learning." *International journal of educational technology in higher education* 18, no. 1 (2021): 54.

[3] Mohamed Hashim, Mohamed Ashmel, Issam Tlemsani, and Robin Matthews. "Higher education strategy in digital transformation." *Education and information technologies* 27, no. 3 (2022): 3171-3195.

[4] Ouyang, Fan, Luyi Zheng, and Pengcheng Jiao. "Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020." *Education and information technologies* 27, no. 6 (2022): 7893-7925.

[5] Mithas, Sunil, Zhi-Long Chen, Terence JV Saldanha, and Alysson De Oliveira Silveira. "How will artificial intelligence and Industry 4.0 emerging technologies transform operations management?." *Production and operations management* 31, no. 12 (2022): 4475-4487.

[6] Chiu, Thomas KF, Qi Xia, Xinyan Zhou, Ching Sing Chai, and Miaoting Cheng. "Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education." *Computers and Education: Artificial Intelligence* 4 (2023): 100118.

[7] Crompton, Helen, and Diane Burke. "Artificial intelligence in higher education: The state of the field." *International journal of educational technology in higher education* 20, no. 1 (2023): 22.

[8] George, Babu, and Ontario Wooden. "Managing the strategic transformation of higher education through artificial intelligence." *Administrative Sciences* 13, no. 9 (2023): 196.

[9] Aldoseri, Abdulaziz, Khalifa N. Al-Khalifa, and Abdel Magid Hamouda. "AI-powered innovation in digital transformation: Key pillars and industry impact." *Sustainability* 16, no. 5 (2024): 1790.

[10] Wang, Shan, Fang Wang, Zhen Zhu, Jingxuan Wang, Tam Tran, and Zhao Du. "Artificial intelligence in education: A systematic literature review." *Expert systems with applications* 252 (2024): 124167.

[11] Singun, Amando Jr. "Unveiling the barriers to digital transformation in higher education institutions: a systematic literature review." *Discover Education* 4, no. 1 (2025): 37.

[12] T. Dinesh and Asst.Prof. Siva Balan, "Sustainable Crop Yield Forecasting Using Advanced Machine Learning Techniques Based on Comprehensive Analysis of Soil Health Parameters and Environmental Factors," Int. J. Adv. Eng. Manag. Syst., vol. 1, no. 1, pp. 41-52, 2025. doi: 10.65379/tpsn2013/ijaemsv01i01p4.

[13] Pilaniwala, Pankaj. "Artificial intelligence in product management: enhancing user experience personalization through GenAI." In *2024 3rd international conference on automation, computing and renewable systems (ICACRS)*, pp. 1135-1140. IEEE, 2024.

[14] Kassaye, Serkalem Negusse. "Application of artificial intelligence in higher education: A systematic review." *Kotebe journal of education* 2, no. 1 (2024): 72-86.

[15] Witkowski, Aron, and Andrzej Wodecki. "Where does AI play a major role in the new product development and product management process?." *Management Review Quarterly* (2025): 1-38.

[16] Quy, Vu Khanh, Bui Trung Thanh, Abdellah Chehri, Dao Manh Linh, and Do Anh Tuan. "AI and digital transformation in higher education: Vision and approach of a specific university in Vietnam." Sustainability 15, no. 14 (2023): 11093.