Enhancing Curriculum Development with Gen AI: Data-Informed Strategies for Academic Leaders

Dr. Nouran Ahmed Nashaat
Assistant Professor
n.a.nashat@aast.edu

Dr. Kesmat Mohamed AbdelAziz
Assistant Professor
Kesmat.yehia@aast.edu

Business Information Systems Department
Arab Academy for Science, Technology & Maritime Transport, Cairo, Egypt

Abstract

The study examines the strategies and models for inclusive use of GenAI for academic leadership and data-informed decision-making in the development of higher education curriculum. Educational institutions need to have an organized structure and leadership support to guide them in the development of their educational design using AI tools and the personalization of learning to create inclusivity. The study employs a comprehensive literature review to identify five key components, including GenAI capability, data-informed strategies, ethical curriculum design, curriculum leadership decision making and curriculum reform. The research provides a conceptual framework that links the five dimensions with a thorough analysis. Both pedagogical coherence and organizational leadership are analyzed within the theoretical framework of the Technological Pedagogical Content Knowledge (TPACK) framework and Transformational Leadership Theory. The research also contains a detailed questionnaire based on validated academic instruments to aid future empirical testing. Academic leaders can leverage ethical and strategic deployment of GenAI to innovate curriculum, as an evidence-based and inclusive approach. The research offers a thorough theoretical background with empirical evidence and insights into the potential of GenAI to revolutionize curriculum in educational Institutions.

Keywords: *Generative AI, Curriculum Development, Data-Informed Strategies, Educational Leadership, Higher Education Reform, Learning Analytics.*

Introduction

As Generative Artificial Intelligence (GenAI) evolves so quickly, higher education is changing in so many ways, especially in curriculum design, teaching approaches, and continuous improvement. Current research suggests that GenAI has the potential to revolutionize the creation of educational content, making it more efficient and creative, and promoting more adaptive and personalized learning experiences (Khamis et al., 2025). The use of GenAI tools can enable faculty to create learning outcomes, assessments, and teaching resources that focus more on student decision making and more complex pedagogical processes. In this regard, GenAI can contribute to enhancing educational quality by introducing automation, interaction, and scalability, representing a crucial element of the technology-driven educational transformation of the curricula (Monzon & Rodriguez, 2024; Kasztelnik, 2024).

At the same time, the use of data is growing in importance in universities to support curriculum design and evaluation. By leveraging learning analytics, AI recommendation systems, predictive modeling, and real-time feedback mechanisms, educators gain insights into student performance and behavior that guide their instruction and help students adapt more quickly. These technologies, such as learning analytics, AI recommendation systems, predictive modeling, and real-time feedback mechanisms, enable educators to

* This article was submitted in March 2026, and accepted for publication in May 2026. Published Online in May 2026.
DOI: 10.21608/aja.2026.479913.2071

make informed decisions about student learning and behavior, optimizing their teaching methods to support faster student adaptation. These approaches enable access to the needs of learners, improve pedagogical approaches, and help design education more closely to the needs of the labor market. This means that data-informed practices facilitate more precise, proactive, and responsive curriculum development, which increases the effectiveness and relevance of the curriculum.

With these developments, we are facing many ethical and governance issues arising from the integration of GenAI and Data Analytics. In the literature, there has been a growing focus on the issues of data privacy, algorithmic bias, transparency, and access inequalities to technology (Chen et al., 2025). If not properly safeguarded, the use of AI in education could exacerbate inequalities and weaken institutional trust. Although the significance of ethical concerns has been recognized in previous studies, they are normally peripheral elements that are viewed as constraints, rather than elements of curriculum design. This narrow view overlooks the importance of ethical considerations in the responsible adoption of AI in the education sector. Therefore, it is crucial to include ethical design principles in the design of curriculum, to create accountability, inclusiveness, and sustainability in the long term (Symeou et al., 2025).

Personalizing the curriculum is another crucial aspect, which has been widely accepted is a major factor that contributes to education transformation. By leveraging GenAI and data analytics, adaptive learning pathways can be created that offer customization of content, pacing, and assessment to the needs of each student (Author, Year). There are indications that this personalization improves students' engagement, motivation, and learning outcomes, as well as fostering their autonomy (Bektik et al., 2024). Current research, however, has focused mainly on personalization without its integration with other aspects of curriculum change. This is a disconnected strategy that doesn't consider interdependencies between personalization, ethical design, and institutional strategy.

Leadership also comes into play as a critical determinant to success in AI-driven innovation in higher education. To develop the technological infrastructure, ethical governance, and encouraging faculty development, effective leadership is needed (Khairullah et al., 2025). Leaders are expected to strike a balance between the opportunities and risks of using technology and ensuring that it is in line with institutional goals. Despite this, the research about the role of leadership as a dynamic enabler linking the technological, pedagogical and ethical aspects of curriculum transformation is not extensively explored in previous studies.

Literature Review

GenAI Capabilities

The integration of Generative Artificial Intelligence (GenAI) in the Higher Education is greatly speeding up the innovation of curriculum across disciplines. Recent studies point to GenAI being a tool that helps to increase the efficiency and creativity of curriculum design by automating the creation of course content, generating learning outcomes, creating assessments, and assisting with course planning (Khamis et al., 2025; Jensen, 2024). GenAI is also beginning to play an increasingly important role in the development of personalised teaching materials, simulation of real-world scenarios and scaffolding student learning, through interactive explanations and personalised feedback (Monzon & Rodriguez, 2024; Kasztelnik, 2024).

In the academic fields of professional, engineering, and data sciences, researchers have suggested that GenAI literacy and GenAI competence should be incorporated into academic programs to ensure that students learn in a manner that is commensurate with the demands of changing industries (Chen et al., 2025; Bakharia & Harrigan, 2024). GenAI-based frameworks have the potential to make problems easier to solve, to provide support to writing and to adaptive learning by helping instructors and learners with complex tasks. These findings collectively place GenAI capabilities as a foundation building enabler of technologically modernized curricula and provide a rationale for exploring the impact of GenAI capabilities on curriculum personalization and ethical curriculum design.

Data-Informed Strategies

A parallel stream of research is focused on the increasing role of data in decision-making in the development of curriculum and instructional plans. The integration of learning analytics and predictive models and AI-driven dashboards helps educators to make informed decisions based on student performance trends, learning behaviors and engagement patterns (Chu & Ha, 2025; Kirange & Patel, 2025).

Data-driven curriculum processes can more effectively make accurate adjustments to curriculum processes using evidence they can collect from the gaps, needs projected and learning outcomes that require alignment with changing needs.

Data informed strategies also facilitate the decision making related to programs at the program level such as curriculum mapping, competency alignment and industry insights integration (Abisoye, 2023; Kamaruddin et al., 2023). Institutions are supported with recommendation systems and tools of automated analysis that help them customize the content and support services to meet the needs of their students to create more dynamic and responsive curricula (Almansour et al., 2025).

Concurrently, in the literature, warnings about the ethical challenges that arise from the growing use of education data, including concerns with privacy, fairness, algorithmic bias and governance (Ngozi et al., 2024; Kurtz et al., 2024). It is argued that these are reasons why it is important to integrate the data-driven approach with the ethical principles for curriculum design. Overall, the studies provide a basis for exploring a data-driven approach as a predictor of personalization and ethics curriculum design in an AI-driven environment.

Ethical Curriculum Design

The adoption of GenAI and data analytics in education has been so swift that there has been a strong need for ethical frameworks in curricula development. The danger lies in the biased outputs, misinformation, compromised academic integrity and unequal access several works have highlighted as chief solutions to addressing the challenge of technology-led learning environments (Symeou et al., 2025; Bektik et al., 2024). Ethical curriculum design involves ensuring the transparency, accuracy, fairness, and accountability of using AI tools, particularly in the development of instructional materials or providing support to the assessment process (Delgado-Ruiz et al., 2024).

Researchers endorse the importance of institutional policies and professional standards addressing issues of privacy, data security, and content validity and human oversight in AI-enhanced learning environments. Ethical design also includes promoting the literacy of AI among students, allowing them to evaluate the results of the AI systems and avoid excessive dependence on such systems (Shimizu et al., 2023; Lee & Lim, 2024).

Given these concerns, designing ethical curricula has become an important part of the challenge of making sure that the AI-enabled educational innovation is trustworthy, equitable, and connected to academic values. It therefore becomes an important concept to consider in terms of how the curriculum can be reformed.

Curriculum Personalization

With the arrival of GenAI and data analytics in the education sector, there has been a growing need to integrate ethical considerations in education curricula. Incorporation of ethical considerations in education curricula has become a need with the advent of GenAI and data analytics in the education sector. The literature continues to stress that, unless explicit and accountable guidelines are implemented, AI-assisted learning spaces may yield biased results, spread misinformation, undercut academic integrity, and achieve inequalities in access. (Symeou et al., 2025; Bektik et al., 2024). The ethical curriculum design suggests transparency, accuracy, fairness, and accountability in the use of AI tools in the creation of instructional materials and/or to support the assessment process (Delgado-Ruiz et al., 2024).

Researchers demand the development of institutional policies and professional standards of such matters as privacy, data security, content validity, and human control in AI assisted learning settings. Ethical design also involves creating AI education and awareness among the students, so that they can question the output of the AI generated systems and not be blinded by dependence on the automated systems (Shimizu et al., 2023; Lee & Lim, 2024).

In these matters, ethical curriculum design is an essential component to ensure the application of AI-enabled educational novelty is reliable, fair, and establishes a lasting academic paradigm. It therefore constitutes a significant construct in appreciating ways of reforming curriculum.

Leadership Decision-Making

Leadership is found to be a key success factor in the use of AI and in the change of curriculum. The adoption of GenAI tools and data-driven approaches should be supported by institutional vision, investment in digital infrastructure, and policies, all of which is the responsibility of the leader as suggested by research (Tarisayi, 2023; Khairullah et al., 2025). It requires effective leadership to address ethical risks, offer faculty professional growth, and develop organizational cultures that are innovative.

It was also found that leaders can facilitate institutional preparedness through framing expectations, maintaining a collaborative governance environment, and managing change resistance (Jenkins & Pierson, 2025; Schmidt & Johnson, 2024). The human-oriented leadership strategies focus on the need to keep human control over things, allow instructors to ensure their independence, and make sure that technological usage does not bypass pedagogical principles and student requirements.

As a result, the decision-making process of the leadership is reported to be a significant source of curriculum change, facilitating the institutions to incorporate GenAI, maintain ethics, and continue with individualized learning programs. It thus forms a major part of the model as it has direct effects on curriculum reform.

Curriculum Reform

Reform of the curriculum in the era of GenAI is gradually being understood as a multidimensional process inflicted by technological competency, information-driven decision-making, ethical administration, pedagogical individualization, and leadership. Research records the way AI-powered tools encourage educators to re-architect course designs, use flexible learning routes, inculcate AI literacy, and incorporate industry-related competencies (Chen et al., 2025; Khamis et al., 2025). Individualized learning, moral principles, and decision-making in instruction that is supported by data are considered one of the primary factors of sustainable reform.

In the literature, curriculum reform is considered a technological and organizational change process, in which there is to be an agreement between the pedagogical goals, the strategies of the institution, and the responsible use of AI. The conceptual foundation of this positioning is the examination of how GenAI capabilities, data-grounded strategies, personalization, ethics, and leadership as a whole play out in the curriculum reform.

Theoretical Foundation

Technological Pedagogical Content Knowledge (TPACK) Framework.

The Technological Pedagogical Content Knowledge (TPACK) framework is a foundational frame of understanding the ways GenAI and data-driven strategies influence the curriculum processes. According to TPACK, successful learning innovation is a product of dynamic interaction of three fundamental areas of knowledge, technological knowledge (TK), pedagogical knowledge (PK), and content knowledge (CK). If these areas are more logically incorporated, technology supports, instead of interrupting, teaching, and learning.

GenAI capabilities, in terms of curriculum development that uses GenAI, depict the domain of technological knowledge, whereby tools may be used to produce learning materials, foster adaptive learning, and facilitate course development. The personalization of the curriculum is compatible with pedagogical knowledge in that; it operationalizes instructional practices that address the differences in learners based on adaptive content, differentiated feedback, and differentiated pathways. The relevance of ethical curriculum design is associated with the content and contextual knowledge regarding the importance of academic rigor, transparency, fairness, and responsible use of AI-generated materials.

TPACK thus facilitates the assumption of the model that the successful integration of GenAI and data-informed practices into the work of the curriculum relies on how they are aligned with pedagogical design and ethical concerns. The studies cited in the uploaded literature show that GenAI integration can only be an educationally valuable object when it is systematically aligned with the pedagogy and disciplinary content, which supports the links between GenAI abilities - personalization of the curriculum and GenAI abilities - design of ethical curriculum, and between the data-based strategies - personalization and ethical practices. By applying the concept of technology as a single element in a larger pedagogical system, TPACK offers the conceptual framework through which the effects of technological and data-driven inputs on curriculum processes can be analyzed and can eventually lead to curriculum reform.

Transformational Leadership Theory

The Transformational Leadership Theory represents a secondary perspective with which leadership decision-making facilitating AI-enabled curriculum reform can be clarified. This theory suggests that transformational leaders encourage and influence members of the organization to be innovative, work towards a shared objective, and transform the way institutions are conducted. They accomplish this by four fundamental behaviors, namely, idealized influence, inspirational and intellectual motivation, and individualized consideration.

Transformational leadership in an AI-integrated educational setting helps to foster a culture that underlies responsible experimentation, ethical technology utilization, and unceasing enhancement. The leaders set the vision for GenAI in the school, communicate the vision and priorities, and create an environment for the faculty to explore new opportunities for teaching and learning.

They challenge the traditional curriculum structure and model, they help teachers to think differently about the structure of the curriculum and the use of AI tools for personalization, and they renew the question of ethics in creating digital content. Transformational leaders at the organizational level develop policies, resource allocation, and training structures that facilitate the coherent and sustainable presence of GenAI and data-informed strategies.

The literature investigated highlights the fact that leadership can impact institutional preparedness to adopt AI, establish a culture of ethical governance, and minimize the uncertainty involved in new technologies. The model is therefore grounded on transformational leadership operating as the connection between leadership decision making , curriculum reform; and transformational leaders are able to lead an institution through technical change, they can lead the faculty towards larger institutional goals, and they can lead the faculty towards larger institutional goals, and they can make AI-enabled curriculum practices count as reform.

TPACK is one of the tools that can be used to explain how the use of GenAI and data-driven practices can impact curriculum processes, while Transformational Leadership Theory offers insights into who can enable responsible implementation of these practices and why the transformation of an institution might occur. Combined, these theories have an integrated conceptual base of the proposed model of GenAI-enabled curriculum reform in higher education.

Research Problem

The literature offers insight into the features of GenAI, data-driven approaches, ethics, and curriculum personalization, but does not present these concepts from an integrated perspective. There is a lack of understanding of the interaction of these elements as part of a unified framework that creates curriculum transformation in higher education. Current research has tended to look at these elements individually rather than how they are interdependent, and how they are aligned by leadership.

This paper proposes a holistic conceptual framework bringing together the capabilities of GenAI, data-informed strategies, ethical curriculum design, and personalisation in one. Ethical design and personalization are identified as central processes in the process of AI-driven transformation, while leadership decision-making is a moderating and enabling process. This research provides a comprehensive and theoretically informed approach to the study, filling the gaps left by previous works by advancing the understanding of how higher education institutions can strategically use AI to foster sustainable, inclusive, and effective curriculum transformation.

Research Objectives

The purpose of this study is to propose and test an integrated model which clarifies how the use of the Generative Artificial Intelligence (GenAI) and data-driven approaches are associated with the reform of higher education curriculum. The study aims at accomplishing the following objectives:

1- To explore how GenAI technologies can be leveraged to enhance personalization and ethical curriculum design in the context of Higher Education.

2- To explore evidence-based decision-making and ethical curriculum design because of data-informed strategies and personalization of curriculum.

3- To investigate the direct impact of curriculum personalization, ethical curriculum design, and leadership decision making on curriculum reform.

4- To examine the mediating role of curriculum personalization and ethical curriculum design between the technological and data-driven inputs and the outcomes of the curriculum reform.

5- To evaluate the impact of academic leadership decision making on curriculum transformation with the help of Artificial Intelligence.

Hypotheses Development

GenAI Capabilities and Curriculum Personalization

Technological pedagogical content knowledge (TPACK) theory suggests that the best way to achieve the integration of technological tools into effective learning is to ensure alignment of the pedagogical approaches with the content knowledge and technological knowledge (Mishra & Koehler, 2006). In this context, GenAI capabilities are used to create adaptation, personalized feedback, and flexible learning pathways that directly contribute to the provision of differentiated learning experiences. Previous research has shown that AI tools enhance student engagement and enable personalized learning experiences (Monzon & Rodriguez, 2024; Kasztelnik, 2024). As a result, GenAI is likely to greatly improve the concept of personalizing the curriculum.

H1: GenAI capabilities have a positive effect on curriculum personalization.

Data-Informed Strategies and Curriculum Personalization

Data-informed strategies offer useful information that enables action to be taken based on performance, engagement, and learning patterns. In the context of the TPACK framework, this information can support the pedagogical decision-making process by helping teachers to modify teaching methods according to evidence (Mishra & Koehler, 2006). Empirical studies indicate that learning analytics and predictive modelling enable adaptive learning environments and individualized learning (Chu & Ha, 2025; Kirange & Patel, 2025). Hence, data-informed strategies are likely to increase curriculum personalisation.

H2: Data-informed strategies have a positive effect on curriculum personalization.

GenAI Capabilities and Ethical Curriculum Design

While GenAI presents a lot of opportunities for innovation, it also poses ethical challenges concerning bias, transparency, and academic honesty. The TPACK model highlights the need for integration of technology with content and context-specific knowledge, as well as consideration of ethical issues (Mishra & Koehler, 2006). The research shows that integrating ethical considerations into the curriculum design of using AI in education is essential to guarantee fairness and accountability (Holmes et al., 2022; Delgado-Ruiz et al., 2024). With the rise of GenAI capability, it is essential to have robust ethical curriculum design practices.

H3: GenAI capabilities have a positive effect on ethical curriculum design.

Data-Informed Strategies and Ethical Curriculum Design

As the need for data-driven decisions increases, there are ethical considerations to weigh in on privacy, governance, and algorithmic fairness. The literature emphasizes the need for ethical principles to guide the use of data, particularly regarding data integrity, and the importance of ensuring that data is used responsibly (Ngozi et al., 2024; Kurtz et al., 2024). In the context of TPACK, the use of data should be aligned with contextual knowledge and content knowledge including ethics (Mishra & Koehler, 2006). As such, there is an expectation that data-informed approaches will positively impact ethical curriculum design.

H4: Data-informed strategies have a positive effect on ethical curriculum design.

Curriculum Personalization and Curriculum Reform

Technology-driven innovation is at its heart linked to a pedagogical process of personalizing the curriculum, which is a key process in educational modernization. Personalized learning environments increase the engagement of students, improve learning outcomes, and increase instructional effectiveness (Pane et al., 2017; Prain et al., 2013). The personalization aspect of the TPACK can be seen as the fusion of pedagogical and technological knowledge. Hence, expectedly, the implementation of curriculum personalization is expected to significantly contribute to the reform of curriculum.

H5: Curriculum personalization has a positive effect on curriculum reform.

Ethical Curriculum Design and Curriculum Reform

Ethical curriculum design ensures the implementation of AI in a way that is fair, transparent, and accountable. In addition to ethical consideration, sustainable and responsible innovation must be underpinned with ethical frameworks but in previous research, ethical frameworks have been found to be more enabling conditions than drivers of transformation (Symeou et al., 2025; Bektik et al., 2024). Theoretically, however, it is expected that ethical curriculum design will be able to improve the results of curriculum reform.

H6: Ethical curriculum design has a positive effect on curriculum reform.

Leadership Decision-Making and Curriculum Reform

Transformational Leadership Theory focuses on the importance of leadership in innovation, vision setting, and change (Bass & Riggio, 2006). Academic leaders are instrumental in connecting the dots of technological use to institutional plans, in faculty development and in dealing with change resistance. Research has shown leadership commitment plays a significant role in the success of educational change efforts (Fullan, 2020; Khairullah et al., 2025). Thus, the role of decision makers in leadership is expected to have a significant impact on curriculum reform.

H7: Leadership decision-making has a positive effect on curriculum reform.

Data-Informed Strategies and Curriculum Reform

Data-informed strategies allow institutions to make evidence-based decisions to make curricula changes that are informed by data and need. Previous studies indicate, however, that their impact on reform can be mediated through pedagogical mechanisms like personalization (Marsh, 2012; Means et al., 2013). In theory, however, data-based practices should lead to curriculum reform, regardless of these points.

H8: Data-informed strategies have a positive effect on curriculum reform.

Mediating Role of Curriculum Personalization

Mediation theory is a pathway through which the effects of independent variables are linked to dependent outcomes via intermediate variables/explainers (Hayes, 2018). One of the crucial paths linking GenAI capabilities and data-informed strategies to curriculum reform is curriculum personalization. Previous research demonstrates that personalized learning is a process that can transform technology into enhanced educational results (Pane et al., 2017).

H9: Curriculum personalization mediates the relationship between data-informed strategies and curriculum reform.

H10: Curriculum personalization mediates the relationship between GenAI capabilities and curriculum reform.

Mediating Role of Ethical Curriculum Design

Ethical curriculum design is expected to function as a mechanism that ensures responsible integration of GenAI and data-driven practices. However, literature suggests that its impact may be more indirect and context-dependent (Holmes et al., 2022). Despite this, it remains theoretically relevant as a mediating construct.

H11: Ethical curriculum design mediates the relationship between data-informed strategies and curriculum reform.

H12: Ethical curriculum design mediates the relationship between GenAI capabilities and curriculum reform.

Research Methodology

The research design followed in this study was a quantitative cross-sectional study aimed at investigating the associations between the GenAI capabilities, data-informed strategies, curriculum personalization, ethical curriculum design, leadership decision-making, and curriculum reform. The framework used to develop the structural model was the TPACK framework and the Transformational Leadership Theory, and the measurement items were based on the reviewed literature that had been already validated. The approach embraced was methodological, which set rigorous guidelines of exploring technologies in education empirically.

Population and Sampling

The population targeted was the faculty members and academic staff members of higher institutions of learning who are actively involved in teaching, course design, curriculum development, or any other academic quality practices. Non-probability purposive sampling method was employed because the respondents had to be familiar with the technology-based teaching or curriculum designing processes. This is a suitable sampling method where the researcher aims at informed participants who have pertinent domain knowledge.

Instrument Development

The instrument used in the survey contained multi-item scale measurements of every construct of the conceptual model. GenAI capabilities, curriculum personalization, data-informed strategies, and ethical curriculum design items and Leadership decision-making and curriculum reform were based on themes and conceptualizations found in the uploaded literature. Every item was designed by a five-point Likert scale (1 to 5) in which strong disagreement to strong agreement was used to create consistency and comparability between constructs.

Certain validity was taken into consideration by matching all items with theoretical definitions (TPACK and Transformational Leadership Theory) and with operationalizations applied to previous empirical research in the uploaded sources. Further specialist screening was performed involving two scholars in the curriculum development and technology-enhanced learning to ensure the clarity of items and the conceptual correspondence.

Common Method Bias

Given that the data for both independent and dependent variables were collected from the same respondents using a single survey instrument, the potential for common method bias (CMB) was carefully considered (Podsakoff et al., 2003). To mitigate this risk, several procedural remedies were implemented. First, respondents were assured of anonymity and confidentiality, which reduces evaluation apprehension and minimizes socially desirable responses. Second, questionnaire items were carefully worded to ensure clarity and avoid ambiguity, thereby reducing measurement error. Third, different scale formats and item structures were applied across constructs to minimize response pattern bias. Finally, the constructs were conceptually separated within the questionnaire to reduce respondents' ability to infer relationships among variables. These procedural strategies are widely recommended to reduce common method variance at the design stage.

Pilot Study

A pilot study was also carried out on 50 respondents before the major data collection to determine the clarity, reliability, and initial format of the measuring tool. The researchers used the pilot study participants to reflect the same population they targeted and sample them from similar institutions of higher learning.

The pilot findings showed excellent internal consistency among constructs, and the Cronbach alpha of the constructs is more than the recommended 0.70. The feedback provided by participants helped to ensure that items are understandable and relevant, and only a few wording adjustments must be made to make them clearer. The pilot study showed the appropriateness of the survey to be deployed in its entirety and assisted in perfecting the final model of measurement.

Data Collection

After the pilot stage, the final questionnaire was e-mailed via institutional mailing lists, professional academic networks, and official digital mail. Participation was on a voluntary basis, and the respondents were assured of confidentiality and anonymity. The use of screening questions also ensured that only those participants who had teaching, curriculum development, or academic leadership duties were those who were able to complete the survey.

Ethical Considerations

Ethical consent was received before collecting data. Participation was voluntary; informed consent was taken, and no identifiable information was captured. The respondents had the freedom to pull out at any point, and all information was analyzed using aggregate form to guarantee privacy.

Data Analysis and Results

The research methodology used to perform the statistical analysis involves a broad approach to the problem to observe the connection between the GenAI capabilities, data-informed strategies, ethical curriculum design, curriculum personalization, leadership decision-making, and curriculum reform in the context of higher education. The analysis is done by using Partial Least Squares Structural Equation Modeling

(PLS-SEM) using SmartPLS Version 3 which is complemented by IBM SPSS Version 29 to do descriptive and inferential statistical operations. This two-software method allows conducting strict analysis of the measurement and the structural aspects of the suggested conceptual framework (Hair et al., 2019).

The study model is based on the complex framework consisting of three independent variables (GenAI Capabilities, Data-Informed Strategies, and Leadership Decision-Making), two mediating variables (Ethical Curriculum Design and Curriculum Personalization) and one dependent variable (Curriculum Reform).

In the theoretical design, this type of design can be used for the investigation of both direct and indirect effects exhaustively, which corresponds to the modern way of studying complex relationships in the research of educational technology adoption (Sarstedt et al., 2021). This analysis is conducted in a systematic manner in several steps such as demographic profiling, validation of the measurement model, direct and indirect effect hypothesis testing as well as structural model analysis with a conclusion of the importance-performance analysis which offers actionable information to the academic leaders.

This study applied a methodological approach to statistical analysis that will facilitate the identification of relationships between the GenAI capabilities, data-informed approaches, ethical curriculum design, curriculum personalization, leadership decision-making and curriculum reform in the context of higher education. The analysis is based on the Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS Version 3 with support of IBM SPSS Version 29 in carrying out descriptive and inferential statistics. This two-software will allow conducting a stringent analysis of both the measurement and structural aspects of the suggested conceptual framework (Hair et al., 2019).

A complex structure is adopted in the research model consisting of three independent variables (GenAI Capabilities, Data-Informed Strategies, and Leadership Decision-Making), two mediating variables (Ethical Curriculum Design and Curriculum Personalization), and one dependent variable (Curriculum Reform). This design enables the examination of direct and indirect impacts in the theoretical framework in a comprehensive way and in line with modern methods of studying complex relationships in educational technology adoption research (Sarstedt et al., 2021). The analysis will be conducted in a systematic manner that involves a series of steps such as demographic profiling, validation of measurement model, test of both direct and indirect effects, and structural model evaluation, which will end up with importance-performance analysis, to give practical information to the academic leaders.

Common method bias was further assessed using the full collinearity approach as recommended by Ned Kock (2015). This method evaluates variance inflation factor (VIF) values for all latent constructs simultaneously, where values below the conservative threshold of 3.3 indicate that common method bias is unlikely to be a serious concern. This approach is particularly suitable in PLS-SEM as it captures both vertical and lateral collinearity, which are indicative of potential method bias.

The results show that all VIF values ranged between 2.45 and 3.11, remaining below the critical threshold. This suggests that multicollinearity and common method variance do not pose a threat to the validity of the findings. Therefore, the results provide strong statistical evidence that common method bias is not a significant issue in this study.

Demographic Analysis

In the demographics of the study participants as shown in Table 1, there are significant aspects of sample representation and composition of the sample. The age distribution indicates

Table (1) Demographic Profiles of the Respondents

Variable	Category	N	%
Age	Under 30	31	15.5%
	30-39	82	41.0%
	40-49	63	31.5%
	50 and above	24	12.0%
Gender	Female	112	56.0%
	Male	87	43.5%
	Prefer not to say	1	0.5%
Academic Rank	Lecturer	38	19.0%
	Assistant Professor	64	32.0%
	Associate Professor	68	34.0%
	Professor	29	14.5%
	Other	1	0.5%
Experience	Less than 5 years	16	8.0%
	5–10 years	25	12.5%
	11–15 years	49	24.5%
	More than 15 years	109	54.5%
	Prefer not to say	1	0.5%
GenAI Tools Usage	Yes	192	96.0%
	No	8	4.0%

a great level of diversity where the highest percentage of the respondents are aged thirty to thirty-nine (41.0%), then forty to forty-nine (31.5%), under thirty (15.5%), and fifty and above (12.0%). This distribution means that the faculty members in their best career phases are strongly represented and, therefore, can have considerable experience in the field of technology integration, yet be still interested in the new educational innovations (Venkatesh et al., 2016).

The sample on gender representation reveals a rather balanced sample where women participants make up 56.0 percent of the respondents and male respondents make up 43.5 percent, and one respondent (0.5) opted out of specifying gender identity. The close-to-equivalent distribution will help increase the generalizability of the findings in gender groups.

The distribution of academic ranks represents a thorough coverage of the faculty ranks with the Associate Professors (34.0 percent), the Assistant Professor (32.0 percent), the Lecturers (19.0 percent), and the Full Professor (14.5 percent) taking the first 4 positions. This sampling is in line with the normal academic workforce makeup and guarantees that the sample used in the research is made up of the views of different career levels (Schein, 2010).

Measurement Model Assessment

Measurement model assessment is a very important initial step in the PLS-SEM analysis and is used to test the validity and reliability of the constructs before testing structural relationships among variables (Hair et al., 2019). This stage determines the validity of the measurement instruments in that they can measure theoretical constructs that they are set up to measure by systematic analysis of indicator loadings, internal consistency reliability, convergent validity, and discriminant validity. In accordance with the traditional models of reflective measurement, the assessment uses a variety of complementary criteria, in order to make sure that the further interpretation of structural model is based on the sound psychometric basis (Sarstedt et al., 2021).

The analysis of loading of indicators as shown in. Figure 1 indicates that all the items exhibit high reliability to measure their constructs. The loading of individual items (0.788 to 0.915) is quite large with all constructs and much higher than the recommended level of 0.70 in established scales (Hair et al., 2021). It shows the maximum loading of Q17, which is Curriculum Reform with 0.915, and the lowest loading of 0.788 under Q8, which is Data-Informed Strategies. The t-values are very significant with p-values of 0.000 and the 95% confidence intervals of loadings do not show the value of 0, which gives strong statistical evidence of the reliability of indicators (Henseler et al., 2015). This trend shows that every item means something and is useful and meaningful to its corresponding construct without any substantial cross-loadings error.

Evaluation of internal consistency reliability using the Cronbach Alpha and Composite Reliability indices demonstrates that all of the constructs are very reliable. Cronbach Alpha values lie between 0.833 and 0.884, and all of them are significantly high at 0.70 and above, which is the recommended minimum. Good reliability is based on 0.80 threshold (Nunnally and Bernstein, 1994). The Cronbachs Alpha of Leadership Decision-Making is the greatest and reaches 0.884 and the lowest yet acceptable value is obtained by Data-Informed Strategies which is 0.833. The Composite Reliability as shown in Table 2 shows the value of the difference load-

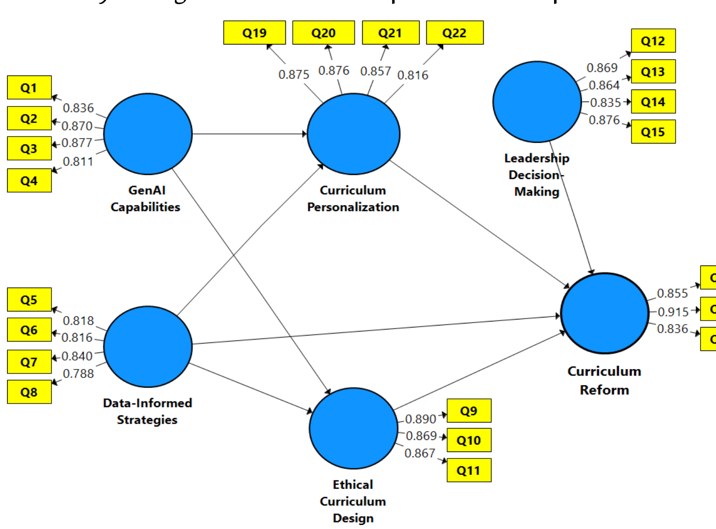

Figure (1) Measurement Model Assessment

ings of indicators, with a range of 0.888 to 0.920 and all of them comfortably above 0.70, which is the threshold of high levels of internal consistency (Bagozzi and Yi, 1988).

Table (2) Reliability and convergent validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
GenAI Capabilities	0.871	0.872	0.912	0.721
Data-Informed Strategies	0.833	0.834	0.888	0.665
Ethical Curriculum Design	0.848	0.85	0.908	0.766
Curriculum Personalization	0.878	0.879	0.917	0.733
Leadership Decision-Making	0.884	0.888	0.92	0.742
Curriculum Reform	0.838	0.845	0.903	0.756

The rho A - coefficient, which is less affected by the count of items and offers an alternative reliability estimation, lies between 0.834 and 0.888, again supporting the reliability results and showing that all measurement scales show strong internal consistency.

Table 3: Discriminant validity

Construct ↔ Construct	HTMT	95% CI for HTMT	
		LL	UL
Curriculum Reform → Curriculum Personalization	0.939	0.862	0.996
Data-Informed Strategies → Curriculum Personalization	0.732	0.536	0.861
Data-Informed Strategies → Curriculum Reform	0.752	0.567	0.878
Ethical Curriculum Design → Curriculum Personalization	0.697	0.499	0.843
Ethical Curriculum Design → Curriculum Reform	0.703	0.518	0.839
Ethical Curriculum Design → Data-Informed Strategies	0.868	0.749	0.963
GenAI Capabilities → Curriculum Personalization	0.722	0.55	0.844
GenAI Capabilities → Curriculum Reform	0.651	0.41	0.818
GenAI Capabilities → Data-Informed Strategies	0.965	0.893	1.0
GenAI Capabilities → Ethical Curriculum Design	0.841	0.694	0.961
Leadership Decision-Making → Curriculum Personalization	0.865	0.743	0.963
Leadership Decision-Making → Curriculum Reform	0.917	0.836	0.98
Leadership Decision-Making → Data-Informed Strategies	0.7	0.512	0.832
Leadership Decision-Making → Ethical Curriculum Design	0.707	0.526	0.848
Leadership Decision-Making → GenAI Capabilities	0.624	0.407	0.79

The Heterotrait-Monotrait (HTMT) ratio of discriminant validity as shown in Table 3 establishes that all constructs are empirically differentiated in each other based on the recent methodological developments on PLS-SEM (Henseler et al., 2015). The majority of the HTMT values are lower than 0.9 conceptually. Similar items, and the largest value is 0.965 of the relationship between GenAI Capabilities and Data-Informed Strategies (Gold et al., 2001). More to the point, analysis of the 95% confidence intervals shows that no 95% interval contains the value of 1.0, which gives solid statistical data of the discriminant validity (Franke and Sarstedt, 2019). The most discriminated constructs are GenAI Capabilities and Curriculum Reform (HTMT = 0.651) and Leadership Decision-Making and GenAI Capabilities (HTMT = 0.624) and the strongest conceptual overlap is observed between GenAI Capabilities and Data-Informed Strategies (HTMT = 0.965), which is theoretically reasonable because of the complementary functions of the constructs in the context of technology-enhanced curriculum development. Overall, the discriminant validity test shows that each construct is measuring a specific aspect of the conceptual framework, and all of them are appropriate in terms of their relationships.

Table (4) Direct Hypothesis Testing

H	Path	B	t-value	P-value	95% BCCI		Remark
					LB	UB	
H1	GenAI Capabilities → Curriculum Personalization	0.354	3.32	0.001	0.141	0.555	Supported
H2	Data-Informed Strategies → Curriculum Personalization	0.336	2.995	0.003	0.117	0.552	Supported
H3	GenAI Capabilities → Ethical Curriculum Design	0.365	3.262	0.001	0.144	0.584	Supported
H4	Data-Informed Strategies → Ethical Curriculum Design	0.437	4.517	0	0.249	0.619	Supported
H5	Curriculum Personalization → Curriculum Reform	0.43	6.108	0	0.291	0.566	Supported
H6	Ethical Curriculum Design → Curriculum Reform	0.007	0.094	0.925	- 0.148	0.133	Not Supported
H7	Leadership Decision-Making → Curriculum Reform	0.385	5.822	0	0.242	0.503	Supported
H8	Data-Informed Strategies → Curriculum Reform	0.127	1.833	0.067	- 0.008	0.263	Not Supported

Direct Effects

The direct hypotheses testing step analyses the structural connections between constructs within the put forward conceptual framework by using path analysis of the PLS-SEM methodology as shown in Table 4. This analysis appraises the size, trend, and difference between the hypothesized direct effects among independent, mediating, and dependent variables, which are statistically significant (Hair et al., 2019). The path coefficients are standardized regression weights used to denote the strength of relationships and bootstrap confidence intervals, and p-values are used to determine statistical significance. The values of R2 that represent the explained variance of endogenous constructs give an indicator of the predictive accuracy of the model and the percentage of variance that the antecedent variables explain (Chin, 1998).

- Hypothesis H1, which suggests a positive relationship between GenAI Capabilities and Curriculum Personalization, has a good level of empirical evidence, having a path coefficient of 0.354 ($t = 3.32$, $p = 0.001$). The 95% bias-corrected confidence interval [0.141, 0.555], excludes the value of zero, which proves the statistical significance and results in the fact that the increased GenAI abilities provide personalized curriculum development methods (Crompton and Burke, 2018).
- Hypothesis H2, which investigates the connection between Data-Informed Strategies and Curriculum Personalization is also supported with a path coefficient of 0.336 ($t = 2.995$, $p = 0.003$) and a confidence interval of [0.117, 0.552] proving that evidence-based decision-making can play a significant role in the process of a curriculum personalization (Means et al., 2013).
- Hypothesis H3, which hypothesizes the impact of the genAI Capabilities on Ethical Curriculum Design, is well supported with path coefficient = 0.365 ($t = 3.262$, $p = 0.001$) and confidence interval = [0.144, 0.584] indicating that the used AI technological capabilities can be utilized to improve ethical considerations in curriculum development in cases where they are well used (Holmes et al., 2022).
- The strongest effect of the relationships that are tested is hypothesis H4, which suggests that Data-Informed Strategies have a positive impact on Ethical Curriculum Design, with a path coefficient of 0.437 ($t = 4.517$, $p < 0.001$) and confidence interval [0.249, 0.619] proving that data-based approaches play an important role in practice related to ethical curriculum design (Williamson, 2017).
- Hypothesis H5, which tests the association between Curriculum Personalization and Curriculum Reform, is strongly supported with path coefficient of 0.430 ($t = 6.108$, $p < 0.001$) and confidence interval of 0.291 to 0.566 indicating that personalized learning strategies should be viewed as important contributors to wider curriculum transformation programs (Prain et al., 2013).
- Hypothesis H7, which is the proposal testing the direct impact of Leadership Decision-Making on Curriculum Reform, is highly supported with the path coefficient of 0.385 ($t = 5.822$, $p < 0.001$) and confidence interval [0.242, 0.503], which proves the idea that proactive leadership commitment has a direct effect on curriculum reform processes (Fullan, 2020). Nevertheless, two hypotheses are not statistically significant.
- The hypothesis H6 which postulates that Ethical Curriculum Design has a positive impact on Curriculum Reform is not supported as the path coefficient of 0.007 ($t = 0.094$, $p = 0.925$) is negligible and falls within the confidence interval of [-0.148, 0.133] which contains 0.
- Likewise, Hypothesis H8, which focuses on the direct effect of Data-Informed Strategies in Curriculum Reform, is not substantiated with path coefficient of less than. 0.127 ($t = 1.833$, $p = 0.067$) and confidence interval [-0.008, 0.263]. Although the p-value is quite close to the significant level, the confidence interval slightly overlaps with that of zero which indicates that Data-Informed Strategies can affect Curriculum Reform, but not directly, but rather indirectly (Preacher and Hayes, 2008).

Hypotheses Testing in the Form of Indirect Hypothesis

Indirect effects analysis is an important part of the mediation analysis shown in Table 5 as it discloses how independent variables affect dependent variables via intermediate relationships but not only through direct relationships (Preacher and Hayes, 2008). This is of significance, especially in complex theoretical models where the mediating variables are postulated to carry the impact of antecedent constructs on outcome variables. The method used in the assessment of indirect effects is bootstrapping that produces bias-corrected confidence intervals to infer the significance and strength of mediated pathways effectively (Hayes, 2018). This understanding of these indirect mechanisms provides a more profound theoretical clarification of how GenAI capabilities and data-informed strategies eventually lead to the outcomes of curriculum reform.

Table (5) Indirect Hypothesis Testing

H	Path	B	t-value	P-value	95% BCCI		Remark
					LB	UB	
H9	Data-Informed Strategies → Curriculum Personalization → Curriculum Reform	0.144	2.517	0.012	0.049	0.27	Supported
H10	GenAI Capabilities → Curriculum Personalization → Curriculum Reform	0.152	2.999	0.003	0.063	0.261	Supported
H11	Data-Informed Strategies → Ethical Curriculum Design → Curriculum Reform	0.003	0.091	0.928	-0.065	0.063	Not Supported
H12	GenAI Capabilities → Ethical Curriculum Design → Curriculum Reform	0.002	0.091	0.928	-0.062	0.048	Not Supported

The indirect effects analysis indicates that there are two important mediated effects, and two of these effects are statistically insignificant.

- Hypothesis H9, which hypothesizes that Data-Informed Strategies moderate Curriculum Reform by Curriculum Personalization has an indirect effect, that = 0.144 (t = 2.517, p = 0.012) with a 95% bias-corrected confidence interval [0.049, 0.270], which is not equal to zero. This observation implies that the data-driven decision-making strategies play a partial role in the curriculum reform because they enable personalized learning strategies, making Curriculum Personalization an important mediating variable in this relationship (Zhao et al., 2010). Although the effect of size is not significant, it shows practical importance in the context of the educational process of transformation.
- Equally, the Hypothesis H10 that addresses the indirect impact of GenAI Capabilities on Curriculum Reform by way of Curriculum Personalization has an indirect effect coefficient of 0.152 (t = 2.999, p = 0.003) and a confidence interval of [0.063, 0.261]. This finding supports the fact that GenAI technological capabilities are used to reform the curriculum by facilitating individualized curriculum development, which creates a theoretically significant mediation channel (MacKinnon et al., 2007). The similar values of H9 and H10 indicate. that both GenAI capabilities and data-informed strategies mediate to have an effect on the outcomes of curriculum transformation in the same way.
- Conversely, Hypothesis H11, which states that Data-Informed Strategies have an impact on Curriculum Reform in terms of Ethical Curriculum Design, is not supported, and has an indirect effect that is insignificant (0.003) with a confidence interval of [- 0.065, 0.063], which contains 0. This null result indicates that there is no significant direct correlation between Ethical Curriculum Design and Curriculum Reform and as such, no opportunities of any significant mediation through this channel (Baron and Kenny, 1986).
- In the same vein, Hypothesis H12, which tests the indirect nature of GenAI Capabilities on Curriculum Reform via Ethical Curriculum Design, does not attain any significance with an indirect effect of 0.002 (t = 0.091, p = 0.928) and confidence interval; -0.062, 0.048. These findings imply that although both GenAI Capabilities and Data-Informed Strategies have a significant impact on the Ethical Curriculum Design, this construct is not an effective vehicle through which the influence can be transferred to Curriculum Reform in the present model specification.

Structural Model

The structural model as shown in Figure 2 and Table 6 test assesses the overall quality and predictive relevance of the PLS-SEM framework more than the measurement model test made previously (Hair et al., 2019). The overall analysis looks at several tests such as the coefficient of determination, the effect sizes, the relevance of the prediction and the variance inflation factors to determine the strength and explanatory capabilities of the structural correlations. All these indicators would tell whether the model exhibits a satisfactory level of fit, the ability to explain the variables significantly, and the absence of problematic multicollinearity that may jeopardize the accuracy of the estimates of path coefficients (Henseler et al., 2016).

Assessment of structural models gives crucial evidence on the ability of the model to explain variance in endogenous constructs and its future ability to give the correct predictions in new samples. The T coefficient of determination values depicts significant explanatory power among the constructs of endogenous variables in the model. The R2 of Curriculum Personalization is 0.434, which implies that both GenAI Capabilities and Data-Informed Strategies alone explain 43.4% of its variance, which is considered a moderate to a strong impact based on the guidelines used by Cohen (1988) to determine the behavioral sciences research. Ethical Curriculum Design has an R2 of 0.586 and this shows that 58.6 percent of its variance is explained by the antecedent constructs which is a high level of variance. However, the particulars of Curriculum Reform are most remarkable as the R2 is 0.736, which means that the model explains 73.6 percent of the variance in this important outcome variable which is quite a strong predictive ability which is well over the norm of typical social science research (Chin, 1998).

The effect size (f2) analysis measures the substantive contribution of each predictor to the total variance that was explained by the endogenous constructs in respect of the criteria of Cohen (1988), 0.02, 0.15, and 0.35 are considered to have a small, medium, and large effect. GenAI Capabilities and Data-Informed Strategies are both of small yet significant impacts on Curriculum Personalization as the outcome, and their f2s are 0.071 and 0.064, respectively. In the case of Ethical Curriculum Design, GenAI Capabilities presents an f2 of 0.103 (small to medium effect) and Data-Informed Strategies presents an f2 of 0.148 (nearing medium effect) meaning that they contribute to this construct to a relatively large extent. In terms of Curriculum Reform, Curriculum Personalization has the highest effect size of f2 of 0.259 (medium-large effect), Leadership Decision-Making f2 of<|human|>Curriculum Reform Curriculum Personalization has f2 of 0.259 (medium to large effect), Leadership Decision-Making f2 of<|human|>Curriculum Reform Curriculum Personalization has the largest effect size of f2 of 0.259 (medium to large effect), Leadership Decision-Making f2 of The direct effect of 0.211 (medium effect) Ethical Curriculum Design (f2 = 0.000), and Data- Informed Strategies (f2 = 0.024) are insignificant, which are in line with the hypothesis test findings.

To the indirect effects, using the adjusted threshold of half the direct effects criteria, both the direct pathways via Curriculum Personalization (H9: f2 = 0.146 and H10: f2 = 0.149) have adjusted small effects that are above the adjusted small effect threshold of 0.01, which means they have significant indirect actions of Curriculum Reform. However, the indirect effects via Ethical Curriculum Design (H11: f2 = 0.003 and H12: f2 = 0.001) are far much less than this value, and they have no practical importance (Kenny, 2018). Stone-Geisser Q2 values are used to measure predictive relevance of the model using blindfolding techniques, positive values in this model show that this model has predictive power beyond that of using simple means (Geisser, 1974; Stone, 1974). Curriculum Personalization has the Q2 of 0.297, Ethical Curriculum Design has the Q2 of 0.434 and Curriculum Reform has the Q2 of 0.536, which are significantly higher in comparison to zero and suggest the high level of predictive relevance.

These values validate that the structural model has significant out-of-sample predictive ability and give credibility to its ability to be applied more generally to other datasets than to the present one (Shmueli et al., 2019). The variance inflation factor analysis indicates that multicollinearity is not a problem in the structural model, as all the values of VIF are at or less than 3.11, a substantial margin lower than the conservative value of 3.3 suggested to be used in PLS-SEM (Hair et al., 2021). The consistency of VIF across all structural paths proves that the predictor variables are independent of each other to a sufficient degree that the estimates of path coefficients are stable and interpretable without the effect of confounding due to too much shared variance among the predictors (Kock and Lynn, 2012). There is no problematic multicollinearity which further gives more belief in the validity and reliability of the structural model findings.

Table (6) Structural Model Assessment Results

H	Path	f-Square	R-Square	VIF	Q-Square
H1	GenAI Capabilities → Curriculum Personalization	0.071	0.434	3.11	0.297
H2	Data-Informed Strategies → Curriculum Personalization	0.064		3.11	
H3	GenAI Capabilities → Ethical Curriculum Design	0.103	0.586	3.11	0.434
H4	Data-Informed Strategies → Ethical Curriculum Design	0.148		3.11	
H5	Curriculum Personalization → Curriculum Reform	0.259	0.736	2.697	0.536
H6	Ethical Curriculum Design → Curriculum Reform	0		2.453	
H7	Leadership Decision-Making → Curriculum Reform	0.211		2.662	
H8	Data-Informed Strategies → Curriculum Reform	0.024		2.501	
H9	Data-Informed Strategies → Curriculum Personalization → Curriculum Reform	0.146		NULL	
H10	GenAI Capabilities → Curriculum Personalization → Curriculum Reform	0.149			
H11	Data-Informed Strategies → Ethical Curriculum Design → Curriculum Reform	0.003			
H12	GenAI Capabilities → Ethical Curriculum Design → Curriculum Reform	0.001			

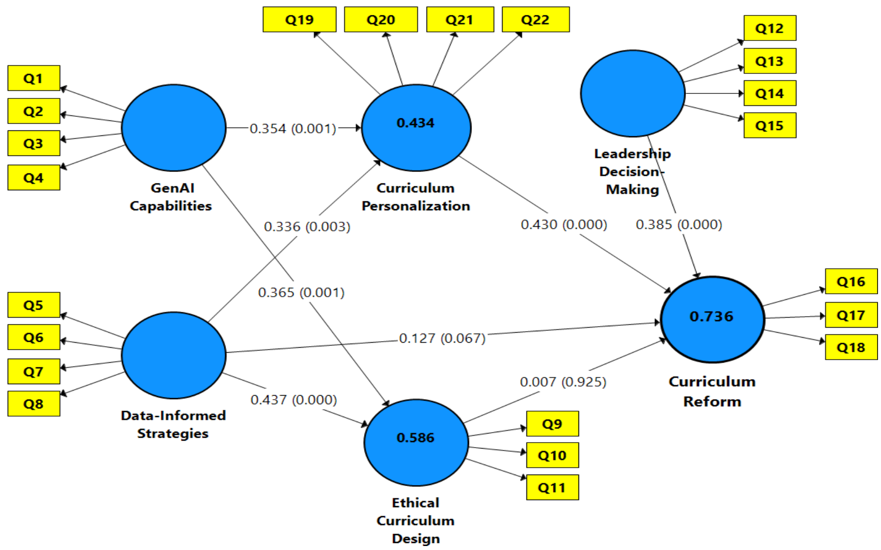

Figure (2) Structural Model

Importance-Performance Map Analysis

Importance-Performance Map Analysis in Figure 3 is a strategic diagnostic tool that is utilized to assess the level of importance of the constructs along with the performance level in predicting the target variable simultaneously, thus indicating areas that require priority actions to be undertaken by the manager and resources distributed (Ringle and Sarstedt, 2016). The method of analysis, which is tailored to the use of PLS-SEM, applies a line plot to demonstrate the overall effect (importance) of constructs versus the overall latent variable scores (performance) to depict which variables are performing well in relation to their importance and which are not performing their part of the work despite their high significance in the model (Hair et al., 2019). The resulting matrix gives the academic leaders useful information to act on as it helps to identify the high-priority improvement areas and those aspects that are performing satisfactorily, thereby enabling evidence-based decision making in curriculum development efforts.

The analysis conducted using importance-performance indicates certain trends of the five antecedent constructs that affect Curriculum Reform. Curriculum Personalization has the highest level of importance of 0.431 meaning that it has a significant overall influence on the Curriculum Reform results. The performance of this construct is also relatively high at 83.161, which implies that personalized learning approaches are already being implemented by institutions with reasonable success. Nevertheless, the highest important

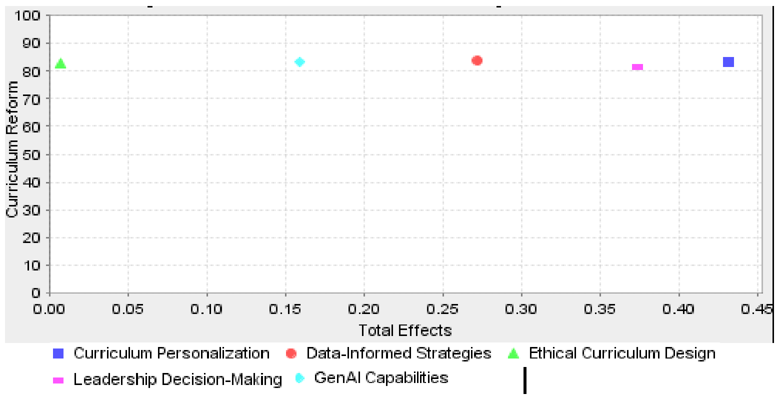

Figure (3) Importance-Performance Map

combined with the performance level lower than some other constructs imply the possibility of further improvement to maximize the results of curriculum reform (Martilla and James, 1977). The second most important one is Leadership Decision-Making with 0.373 indicating that this area has a big influence on curriculum transformation initiatives. This means that there may be a discrepancy between the critical nature of leadership commitment and its actual implementation effectiveness as its performance level is 81.549, which is the lowest among all constructs. It can be inferred that leading engagement and decision-making processes could be an area of high priority in terms of the institutional development since any improvement in this area could lead to a significant payoff in the effectiveness in curriculum reform since it is an area of great significance (Slack, 1994). Data-Informed Strategies has a moderate value of 0.272 and the best level of performance of 83.772, which denotes that the institutions have been able to practice evidence-based decision-making. Such a positive performance compared to importance indicates that data analytics abilities are properly established in the surveyed institutions. GenAI Capabilities demonstrates relatively low significance at 0.158 with an operating level of 83.060, which is that although the technological capabilities are evidently developed, there is less direct influence on curriculum reform in comparison with other factors, which are intermediated by the mediation analysis (Dwivedi et al., 2023). However, most importantly, Ethical Curriculum Design exhibits the least significance at. 0.006 and performance level of 82.775, which indicates that this term is negligible in the contribution of Curriculum Reform as was put in the hypothesis test. Although institutions are keeping a sufficient level of ethical standards in the curriculum design, this construct is not a productive force of curriculum change in the existing model structure. These patterns are also confirmed visually through the importance-performance map where constructs are concentrated in the high-performance area and diverge in their significance dimensions indicating that Curriculum Personalization and Leadership Decision-Making are the areas where the institutions should focus on to achieve better curriculum reform outcomes (Ringle and Sarstedt, 2016).

Discussion

This extensive statistical review gives a solid empirical support concerning the mechanisms, by which GenAI abilities, data-driven policies, and leadership decision-making has an impact on curriculum change in colleges and universities. The research utilized the information on two hundred academic professionals mostly experienced faculty members with a high level of exposure to GenAI technologies, thus guaranteeing the knowledgeable outlooks on technology-enhanced curriculum development practices. The strict analytical methodology, which involves descriptive statistics, validation of measurement models, structural equation modeling, and importance-performance analysis, provides theoretically relevant and practically important results that contribute to the development of knowledge about the processes of curriculum transformation in the digital era. The assessment of measurement model validates the psychometric integrity of all research instruments with the indicators' loadings ranging between 0.788 to 0.915, the composite reliability measure of over 0.888, and the mean variance extracted of all constructs of more than 0.665. Discriminant validity is determined when HTMT ratios are below critical values to guarantee constructs measure different theoretical dimensions. The results give an assurance that the next interpretation of the structural model is based on valid and reliable measurements (Hair et al., 2019). The descriptive statistics indicate that the mean values of all the constructs are high, between 4.263 and 4.347 based on five-point scales, which means that the institution is highly committed to GenAI integration, data-driven decision-making, ethical considerations, curriculum personalization, leadership engagement, and reform initiatives. Correlation analysis proves that there are significant positive correlations among all constructs with the strongest being established between Curriculum Personalization and Curriculum Reform, GenAI Capabilities and Data-Informed Strategies, and Leadership Decision-Making and Curriculum Reform which shows preliminary support of the theoretical framework. The structural model is shown to have a significant explanatory power as it explains 43.4 percent of the variance in Curriculum Personalization, and 58.6 percent in Ethical Curriculum. Design, 73.6 per cent in Curriculum Reform. Direct hypothesis testing indicates that GenAI Capabilities and Data-Informed Strategies have an important effect on both Curriculum Personalization and Ethical Curriculum Design, whereas Curriculum Personalization and Leadership Decision-Making are important direct predictors of Curriculum Reform. Markedly, neither Ethical Curriculum Design nor Data-Informed Strategies manifest any significant direct impacts on Curriculum Reform and therefore indicate that their effects have a strong impact on Curriculum Reform only through indirect means (Sarstedt et al., 2021). The mediation analysis proves the presence of two substantial indirect relationships, demonstrating that both Data-Informed Strategies and GenAI Capabilities have an impact on Curriculum Reform via Curriculum Personalization, the strength of which is 0.144 and. 0.152 respectively. The findings affirm Curriculum Personalization as an essential mediation unit through which the impact of technological abilities and evidence-based practices are relayed to results of curriculum change. Conversely, Ethical Curriculum Design does not act as an important mediator as seen by insignificant indirect effects on both antecedent pathways. These findings imply that although the ethical aspects are significant in the processes of curriculum design, they do not directly influence the speed or scope of curriculum reform efforts (Hayes, 2018). The quality indicators of the structural model support the strength of these results, and the values of predictive relevance amount to 0.297 to 0.536, which is significantly greater than the level of meaningful prediction. The analysis of effect size shows that Curriculum Personalization has the most significant impact on Curriculum Reform, followed by Leadership Decision-Making, other constructs have the effect mainly through indirect means, or have insignificant effects. The fact that all the path coefficient estimates are stable and interpretable is due to the absence of multicollinearity that was verified by using the maximum VIF values of 3.11. The importance-performance analysis delivers strategic guidance to the institutional leaders with Curriculum Personalization being the number one priority construct because it has a high importance level and a moderate level of performance. Leadership Decision-Making turns out to be the area which should be improved as it is of high significance and has the lowest outcomes of all the constructs. The results indicate that higher education institutions should focus on enhancing leadership devotion to technology adoption and the further development of individualized study programs to make the most out of curriculum reform success (Ringle and Sarstedt, 2016). The theoretical value of the research lies in the fact that it expands on the theoretical frameworks by empirically confirming the complicated associations among the GenAI capabilities, data-informed strategies, ethical issues, personalization processes, and curriculum reform outcomes. The results purchase the Technological Pedagogical Content Knowledge framework by showing that effective technology integration is not only the technical abilities but also should be accompanied by the pedagogical changes through individualization and organizational support in the form of leadership commitment (Mishra and Koehler, 2006). The findings are congruent with the Transformational Leadership Theory in that, active decision-making in leadership directly promotes curriculum innovation over the effects of the technological and strategic factors (Bass and Riggio, 2006). The implications of the research in practice imply that academic executives must pursue multidimensional strategies to reform the curriculum that improves GenAI proficiencies, advances data analytics infrastructure, improves personalization processes, and promotes leadership devotion to innovation. Instead of assuming a direct change through technological investments or ethical frameworks, institutions need to acknowledge the fact that curriculum reform can be developed through the mediating channels of personalized learning practices and must be driven through leadership efforts. The results also suggest that ethical curriculum design is crucial to responsible AI integration, but its effect on reform outcomes works not in every way as represented in the current model, which needs further study in future research. Furthermore, common method bias was addressed using both procedural and statistical approaches, and the results confirm that it does not threaten the validity of the findings, thereby strengthening the robustness and credibility of the study.

Discussion of Insignificant Findings

The findings of this research indicated that there were several statistically non-significant relations that needed to be interpreted theoretically as opposed to being discarded. Particularly, there was no significant direct effect of Ethical Curriculum Design on Curriculum Reform since H6 was not supported by a very small path coefficient of 0.007, t-value of 0.094, and p-value of 0.925. On the same note, Data-Informed Strategies did not directly affect Curriculum Reform significantly since H8 was not supported with a path coefficient of 0.127, t-value of 1.833, and p-value of 0.067. Though the effect of Data-Informed Strategies was less than the conventional significance level, its confidence interval was within the range of zero, which means that the direct relationship could not be statistically proved.

It is especially significant that the Ethical Curriculum Design has an insignificant relationship with Curriculum Reform. This fact does not mean that it is not important to design ethical curriculums. Instead, it implies that ethical considerations might not necessarily have any observable curriculum reform outcomes unless they are converted into practical pedagogical, organizational, or leadership practices. Ethical curriculum design can be applied in the context of higher education leveraging GenAI to promote responsible AI use, fairness, transparency, privacy safeguarding, academic integrity, and accountability. Nevertheless, these ethical principles do not necessarily result in the transformation of the curriculum unless accompanied by the mechanisms of implementation including faculty training, institutional policy enforcement, quality assurance systems and the commitment of the leadership.

This reading goes in line with the larger trend of findings. GenAI Capabilities and Data-Informed Strategies were both important predictors of Ethical Curriculum Design, with Data-Informed Strategies appearing to have the strongest direct correlation with Ethical Curriculum Design. This suggests that institutions that have higher data-informed practices and GenAI abilities are more inclined to listen to ethical curriculum design. But the lack of a notable route between Ethical Curriculum Design to Curriculum Reform indicates that ethical awareness might not be adequate to bring about structural change in curricula. That is, ethics might be able to influence the quality, legitimacy, and acceptability of AI-enabled practices in curriculum, but it may not be able to independently determine whether reform takes place.

This interpretation is further supported with the indirect effects. The mediation paths between Ethical Curriculum Design were not significant: Data-Informed Strategies → Ethical Curriculum Design → Curriculum Reform was not supported either. In comparison, the indirect paths via the Curriculum Personalization were important to both Data-Informed Strategies and GenAI Capabilities. This implies that when GenAI and data-informed approaches are translated to tangible individualized learning practices, there are higher chances of curriculum reform, as opposed to when they are simply linked to ethical design principles.

The Data-Informed Strategies direct effect on Curriculum Reform is insignificant and as such deserves attention too. Though the use of data-informed strategies should theoretically be expected to guide the decision-making process in curriculum, the findings indicate that the utilization of data alone does not directly reform the curriculum. Information can be used in evidence, identification of gaps, support of student profiling, and inform decision-making, although it must be pedagogically interpreted and applied in practice before it can produce reform outcomes. This is justified by the high level of indirect impact of Data-Informed Strategies on Curriculum Reform in terms of Curriculum Personalization. Thus, the data seem to play an indirect role: personalization is supported by data, and personalization, in turn, promotes reform.

This observation indicates the gap between having data and utilizing data in a way that facilitates curriculum change. Learning analytics, performance indicators, student feedback, and labor market insights are potentially collected by institutions, but need to be incorporated into curriculum redesign processes. Only when it is converted to adaptive learning pathways, differentiated assessment practices, student-centered content design, and evidence-based pedagogical interventions, data-informed strategies become reform-oriented. The non-significant direct result, therefore, indicate a disconnect between data availability and data-driven curriculum action.

Reinforcement of this explanation is the structural model results. Curriculum Personalization produced the largest effect size on Curriculum Reform whereas Leadership Decision-Making had a significant effect as well. Conversely, Ethical Curriculum Design had an effect size of zero and Data-Informed Strategies had only a small effect size on Curriculum Reform. It means that not only technological or ethical impulse drivers, but practice-oriented and leadership-oriented mechanisms that transform a technological potential into a change in the institutions are the most influential reform drivers in the model.

Overall, the insignificant results provide an important contribution to the study. They demonstrate that the reform of the curriculum enabled by GenAI is not attained only due to the implementation of ethical systems or the collection of educational data. Rather, reform relies on the capability of institutions to transform GenAI capabilities and data-informed insights into personalized curriculum practices and make sure that there is strong leadership direction. In line with this, ethical curriculum design and data-informed strategies are to be considered the more remote causes of curriculum reform, whereas curriculum personalization and leadership decision-making seem to be seen as the more immediate drivers behind curriculum reform. This reading reinforces the theoretical claim that AI-mediated curriculum change is a process that is mediated and embedded in organization, not a technological deliverable.

Conclusion

In this paper, we have thoroughly discussed the relationship between the capabilities of GenAI, data-based approaches, approaches for personalization processes, approaches for developing curriculum in an ethical manner and the leadership decision making process itself to reform the curriculum in higher education. The results are quite compelling to support the hypothesis of a model in which the impact of GenAI and data analytics is mediated by the personalization of curriculum, and that this personalization has the greatest ability to predict and mediate reform. Although some effects of the ability of GenAI and data-driven approaches have been found in the field of ethical curriculum design, the design does not have any predictive power regarding curriculum reform, suggesting ethical issues are a structural need rather than change agents. An important and defining role is played by leadership decision making, which is an indication that technological change in education can only take place with strategic direction, institutional support and an attitude of openness to innovation. The results suggest that the four factors of technological, pedagogical, ethical and organizational are positively related in promoting AI-enabled curriculum reform, as the model explains 73.6 per cent of the variance. A combination of TPACK and Transformational Leadership Theory gives an excellent conceptual framework explaining the pedagogical processes and the leadership circumstances that are required to make GenAI adoption successful. Overall, the work provides an approved form of thinking about how the institutions might instead choose to steer clear of ad hoc AI experimentation, and instead pursue systematic, sustainable curriculum change.

Implications

The results of this study can have several theoretical, practical, and policy implications in terms of higher education institutions that are going through GenAI-enabled curriculum transformation. The results align with the main tenets of TPACK in that the technological supports, such as GenAI tools, can play a vital role in pedagogical outputs, particularly in the personalization of content, when used in an integrated manner in instructional design in theory. The importance of personalization as a predictor, as well as a mediator, suggests that personalization plays a key role in operationalizing technology enhanced change in curriculum. In this context, the key role of leadership decision making in making the curriculum change is continued to the Transformational Leadership Theory, which empirically confirmed the necessity of visionary, supportive leadership to bring the technological potential to the tangible products of the institution. In practical terms, the results highlight that two levers-personalization of the curriculum and the leadership decision-making are the two most powerful drivers in speeding up the process of curriculum reform. The organizations that want to combine GenAI and data-driven practices cannot be guided only by the introduction of technology solutions; they need to develop learning systems in which individualized, adaptive patterns will be embedded in the organization. This requires it to invest in the use of AI-powered learning systems, professional development focused on creating flexible materials and support for data-driven teaching practices. The importance-performance analysis also highlights the fact that though the institutions have made steps to personalization; there is still a discrepancy between the performance of the leadership in relation to the level of its importance. It suggests a need for capacity building within the deans, program coordinators and academic leaders to foster a more technologically savvy, change management, and pedagogically competent outlook on how to integrate AI ethically. The findings of the non-significant direct effect of information-driven strategies and ethical curriculum design on curriculum change suggests that the two factors, although very important, do not significantly influence transformational change on their own. It is, therefore, necessary for the policymakers to think about ethics and data governance as the conditions for more approaches of leadership and pedagogy. While their effects might be indirect, it is important that clear guidelines of ethical use of AI are established, that data literacy is promoted within the faculty, and that governance is strengthened. In general, the findings suggest a multi-level approach based on the combined technological investment with leadership training, faculty training, and pedagogical redesign.

Recommendations

The findings of this study give a number of avenues through which future research can be conducted. To begin with, the insignificant role of ethical curriculum design in forecasting reform implies that one should consider other conceptualizations or other mediators. Future research can investigate whether ethics has an indirect contribution to it using some constructs like trust, institutional legitimacy, or faculty acceptance of AI. Second, qualitative or mixed-method studies may offer more information on the reasons that some processions such as data-informed strategies - curriculum reform- continue to be weak or non-significant, despite theoretical anticipations. Third, longitudinal research might improve the knowledge of GenAI implementation changes over time and whether personalization and leadership impact is stronger or weaker as institutions become more mature and integrated with AI. Fourth, future studies can also compare various institutional contexts, such as a public and a private university, technologically advanced and resource-constrained environments, or regions with different regulatory climates to determine how general the model is. Lastly, the new GenAI approaches like multi-moderation, automatic content-generation, and AI-based quality-assurance systems should be explored as novel constructs that can transform the process of curriculum design and leadership practices.

Research Limitations

Irrespective of theoretical and empirical contributions of this study, it is important to note some limitations. To start with, the research design was a quantitative cross-sectional design which entails the perception of the respondents at one point in time. Although this design is suitable in investigating the relationships among the capabilities of GenAI, data-informed strategies, curriculum personalization, ethical curriculum design, leadership decision-making, and curriculum reform, it does not allow establishing causal relationships or observing how these relationships change over time. Since the impact of GenAI capabilities, leadership decision-making, and personalization may either intensify or diminish with the level of digitization in higher education, longitudinal research would be of interest to determine whether the impact of GenAI capabilities, leadership decision-making, and personalization positively or negatively changes as institutions become more digitally mature.

Second, the study was based on purposive sampling in that the study targeted faculty members and academic staff engaged in teaching, curriculum development, or academic quality practices. Even though this strategy guaranteed that the respondents had the relevant knowledge on the topic of enhanced technology curriculum development, it might limit the extent to which the respondents can be generalized to larger population groups in higher education. The results might not be completely reflective of the perspectives of students, administrative leaders, or policymakers; or institutions that have limited exposure to GenAI tools. This especially applies to the fact that the demographic findings indicated that 96% of the respondents reported having used GenAI tools, meaning that the sample might be representative of a high level of awareness and readiness of AI usage.

Third, the research relied on self-reported survey data which can be influenced by response bias, social desirability bias or subjective interpretation of GenAI-related practices by the respondents. Though the study employed procedural and statistical remedies of common method bias, and the complete collinearity analysis revealed that VIF values were still less than the recommended value. The evidence could be reinforced by future research that may utilize objective institutional evidence, interviews, curriculum documents, learning analytics records, or case study evidence.

Fourth, the research was based on a particular conceptual model, which was founded on TPACK and Transformational Leadership Theory. Although these theories offer a good basis of explaining the technology-enabled curriculum reform and leadership-driven change, other theoretical perspectives can offer more explanatory power. As an illustration, future researchers might incorporate an institutional theory, technology acceptance models, organizational readiness theory, or diffusion of innovation theory to better understand how GenAI-enabled curriculum practices are adopted, normalized, and governed by universities.

Fifth, the ethical curriculum design operationalization might not have fully reflected the institutional and cultural aspects of ethics in AI-enabled education. Ethical curriculum design in this study had a significant impact on curriculum reform both directly and indirectly via the established pathways of the experiment. This implies that ethics can serve as more of an enabling state, a control mechanism, or an institutional protective measure as opposed to being more of a driver of reform. Further studies should thus focus on investigating whether the design of the ethical curriculum influences reform in terms of other factors such as institutional trust, faculty acceptance, student confidence, policy maturity, or perceived legitimacy.

Lastly, despite the high explanatory and predictive relevance of the structural model, with the curriculum reform reported to have a high explained variance, the findings could be discussed within the confines of the chosen sample, constructs, and methodology. Others that might have contributed to curriculum reform, such as institutional culture, digital infrastructure, funding availability, faculty's digital competence, student readiness, regulatory pressure, and resistance to change were not mentioned. The research can also be extended in the future through the introduction of these contextual variables into the model to gain a more broad-based insight into the topic of GenAI-enabled curriculum transformation.

References

- Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. ***Journal of the Academy of Marketing Science***, 16 (1), 74-94. https://doi.org/10.1007/BF02723327
- Bakharia, A. & Abdi, S. (2024). Shaping programming and data science education: Insights from GenAI technical book trends. ***2024 IEEE International Conference on Advanced Learning Technologies (ICALT)***, pp. 116-120, DOI Bookmark: 10.1109/ICALT61570.2024.00040
- Bektik, D. and Others. (2024). ***AI-Powered Curricula: Unpacking the Potential and Progress of Generative Technologies in Education***. Ubiquity Proceedings. P. 38, DOI: 10.5334/uproc.160
- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. ***Journal of Personality and Social Psychology***, 51 (6), 1173-1182.
- https://doi.org/10.1037/0022-3514.51.6.1173
- Bass, B. M., & Riggio, R. E. (2006). ***Transformational Leadership.*** (2nd ed.). Psychology Press. https://doi.org/10.4324/9781410617095
- Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), ***Modern Methods for Business Research.*** pp. 295-336. Lawrence Erlbaum Associates.
- Cohen, J. (1988). ***Statistical Power Analysis for the Behavioral Sciences.*** (2nd ed.). Lawrence Erlbaum Associates.
- Crompton, H., & Burke, D. (2018). The use of mobile learning in higher education: A systematic review. ***Computers & Education***, 123, 53-64. https://doi.org/10.1016/j.compedu.2018.04.007
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. ***MIS Quarterly***, 13 (3), 319-340.https://doi.org/10.2307/249008
- Delgado-Ruiz, R., et al. (2024). Generative artificial intelligence (Gen AI) in dental education: Opportunities, cautions, and recommendations. ***Journal of Dental Education***. 89 (1):130-136. https:// DOI: 10.1002/jdd.13688
- Duca, A. L. (2024). Using Retrieval Augmented Generation to Build the Context for Data-Driven Stories, In: ***Proceedings of the 19th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2024)*** – Vol. 1, pp. 690-696. DOI: 10.5220/0012419700003660
- Dwivedi, Y. K., and Others. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. ***International Journal of Information Management***, 71, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642
- Field, A. (2018). ***Discovering Statistics Using IBM SPSS Statistics.*** (5th ed.). Sage Publications.
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. ***Journal of Marketing Research***, 18(1), 39-50. https://doi.org/10.1177/002224378101800104
- Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: A comparison of four procedures. ***Internet Research***, 29 (3), 430-447. https://doi.org/10.1108/IntR-12-2017-0515
- Fullan, M. (2020). Leading in a culture of change. ***Educational Leadership***, 77 (8), 12- 18.

- Geisser, S. (1974). A predictive approach to the random effect model. ***Biometrika***, 61 (1), 101-107. https://doi.org/10.1093/biomet/61.1.101
- Gold, A. H., Malhotra, A., & Segars, A. H. (2001). Knowledge management: An organizational capabilities perspective. ***Journal of Management Information Systems***, 18 (1), 185-214. https://doi.org/10.1080/07421222.2001.11045669
- Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2019). ***A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*** (2nd ed.). Sage Publications.
- Hair, J. F., Hult and Others. (2021). ***Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook***. Springer Nature. https://doi.org/10.1007/978-3-030-80519-7
- Hayes, A. F. (2018). ***Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-based Approach.*** (2nd ed.). Guilford Press.
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS ath modeling in new technology researUch: Updated guidelines. ***Industrial Management & Data Systems***, 116 (1), 2-20. https://doi.org/10.1108/IMDS-09-2015-0382
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. ***Journal of the Academy of Marketing Science***, 43 (1), 115-135. https://doi.org/10.1007/s11747-014- 0403-8
- Holmes, W. and Others. (2022). Ethics of AI in education: Towards a community-wide framework. ***International Journal of Artificial Intelligence in Education***, 32 (3), 504-526. https://doi.org/10.1007/s40593-021-00239-1Kenny, D. A(2018)
- Johnson, M. (2024). Generative AI and CS Education, ***Communications of the ACM***, Vol. 67, Issue 4, pp. 23-24. https://doi.org/10.1145/3632523
- Kamaruddin, N., et al. (2023). Enhancing Talent Development Using AI-Driven Curriculum-Industry Integration. ***Environment-Behaviour Proceedings Journal***, Vol. 8 No. 26. Doi: https://doi.org/10.21834/e-bpj.v8i26.5129
- Kasztelnik, K. (2024). Artificial Intelligence-Assisted Curriculum Development: Innovations in Designing Educational Content for the 21st Century Learner. ***Journal of Higher Education Theory and Practice***, Vol. 24, No. 11. Doi: https://doi.org/10.33423/jhetp.v24i11.7367
- Kurtz, G. and Others. (2024). Strategies for Integrating Generative AI into Higher Education: Navigating Challenges and Leveraging Opportunities. Education sciences, Vol. 14, No. 5. https://doi.org/10.3390/educsci14050503
- Kline, R. B. (2016). ***Principles and Practice of Structural Equation Modeling.*** (4th ed.). Guilford Press.
- Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. ***International Journal of e-Collaboration***, 11 (4), 1-10. https://doi.org/10.4018/ijec.2015100101
- Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance- based SEM: An illustration and recommendations. ***Journal of the Association for Information Systems***, 13 (7), 546-580. https://doi.org/10.17705/1jais.00302
- Lee, S. S. and Others. (2024). Harnessing Generative AI (GenAI) for Automated Feedback in Higher Education: A Systematic Review. ***Online Learning Journal***, Vol. 28, No. 3. Doi: https://doi.org/10.24059/olj.v28i3.4593
- MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. ***Annual Review of Psychology***, 58,593-614.https://doi.org/10.1146/annurev.psych.58.110405.085542

- Marsh, J. A. (2012). Interventions promoting educators' use of data: Research insights and gaps. ***Teachers College Record***, 114 (11), 1-48.
- https://doi.org/10.1177/016146811211401106
- Martilla, J. A., & James, J. C. (1977). Importance-performance analysis. ***Journal of Marketing***, 41 (1), 77-79. https://doi.org/10.1177/002224297704100112
- Means, B., Padilla, C., & Gallagher, L. (2013). ***Use of Education Data at the Local Level: From Accountability to Instructional Improvement***. US Department of Education, Office of Planning, Evaluation and Policy Development.
- Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. ***Teachers College Record***, 108 (6), 1017-1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x
- Ngozi, B., and Others. (2024). Leveraging Artificial Intelligence for an inclusive and diversified curriculum. ***World Journal of Advanced Research and Reviews***, May,(Vol. 30, No. 2). https://doi.org/10.30574/wjarr.2024.23.2.2440
- Nunnally, J. C., & Bernstein, I. H. (1994). ***Psychometric theory*** (3rd ed.). McGraw-Hill.
- Pane, J. F., Steiner, E. D., Baird, M. D., & Hamilton, L. S. (2017). ***Continued Progress: Promising Evidence on Personalized Learning***. RAND Corporation. https://doi.org/10.7249/RR1365
- Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. ***Journal of Applied Psychology***, 88 (5), 879-903.
- https://doi.org/10.1037/0021-9010.88.5.879
- Prain, V., Cox, P., Deed, C., Dorman, J., Edwards, D., Farrelly, C., Keeffe, M., Lovejoy, V., Mow, L., Sellings, P., Waldrip, B., & Yager, Z. (2013). Personalised learning: Lessons to be learnt. ***British Educational Research Journal***, 39 (4), 654-676. https://doi.org/10.1080/01411926.2012.669747
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. ***Behavior Research Methods***, 40 (3), 879-891. https://doi.org/10.3758/BRM.40.3.879
- Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis, ***Industrial Management & Data Systems***, 116 (9), 1865-1886. https://doi.org/10.1108/IMDS-10-2015-0449
- Sarstedt, M., Hair, J. F., Nitzl, C., Ringle, C. M., & Howard, M. C. (2021). Beyond a tandem analysis of SEM and PROCESS: Use of PLS-SEM for mediation analyses, ***International Journal of Market Research***, 62 (3), 288-299.
- https://doi.org/10.1177/1470785320915686
- Schein, E. H. (2010). ***Organizational Culture and Leadership.*** (4th ed.). Jossey-Bass.
- Schmidt, G. B., and Others. (2024). Considerations of Using Generative Artificial Intelligence in an Academic Leadership Role. ***The Department Chair***, Vol. 35, No. 1. Pp. 14-16.
- Shimizu, I., and Others. (2023). Developing Medical Education Curriculum Reform Strategies to Address the Impact of Generative AI: Qualitative Study. ***JMIR Medical Education***, Nov. 30: 9, Doi: 10.2196/53466.
- Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle,
- C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. ***European Journal of Marketing***, 53 (11), 2322-2347.

- https://doi.org/10.1108/EJM-02-2019-0189
- Slack, N. (1994). The importance-performance matrix as a determinant of improvement priority. ***International Journal of Operations & Production Management***, 14 (5), 59-75. https://doi.org/10.1108/01443579410056803
- Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. ***Journal of the Royal Statistical Society: Series B (Methodological)***, 36 (2), 111-133. https://doi.org/10.1111/j.2517-6161.1974.tb00994.x
- Tabachnick, B. G., & Fidell, L. S. (2019). ***Using Multivariate Statistics.*** (7th ed.). Pearson.
- Tarisayi, K. S. (2023). Strategic leadership for responsible artificial intelligence adoption in higher education. ***CTE Workshop Proceedings***, 11:4-14. DOI:10.55056/cte.616
- Venkatesh, V., Thong, J. Y., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. ***Journal of the Association for Information Systems***, 17 (5), 328-376. https://doi.org/10.17705/1jais.00428
- Williamson, B. (2017). ***Big Data in Education: The Digital Future of Learning, Policy and Practice***. Sage Publications.
- Zhao, X., Lynch Jr, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. ***Journal of Consumer Research***, 37 (2), 197-206. https://doi.org/10.1086/651257