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دور توظيف الذكاء الاصطناعي التوليدي في تعزيز كفاءات القيادات الاكاديمية الرقمية: دراسة استطلاعية لأراء عينة من القيادات الاكاديمية في جامعة ميسان

م.د محمد رؤوف الموسوي[1] م.د انتصار عباس جبر العوادي[2] ا.م.د محمد احمد وهم[3]

جهة الانتساب

قسم إدارة الاعمال/ كلية الإدارة والاقتصاد/ جامعة ميسان[1]
قسم تقنيات إدارة المواد/ كلية البوليتكنك/ الجامعة التقنية الجنوبية[2]
قسم إدارة الاعمال/ كلية الإدارة والاقتصاد/ جامعة ميسان[3]

E-mail

mohamed@uomisan.edu.iq
enteabas@gmail.com
mohammedwaham@uomisan.edu.iq

Affiliation

Department Business Administrator/ College of Administration and Economics/ University of Misan[1]

Department of Materials Management Technologies/ Polytechnic College/ Southern Technical University[2]

Department Business Administrator/ College of Administration and Economics/ University of Misan[3]

المستخلص

هدفت الدراسة إلى تحليل العلاقة بين توظيف الذكاء الاصطناعي التوليدي وكفاءات القيادة الأكاديمية الرقمية لدى القيادات الأكاديمية في جامعة ميسان العراقية. اعتمدت تصميمًا كميًا مقطعيًا من نوع المسح، واستخدمت أسلوب الحصر الشامل؛ لمحدودية المجتمع الدراسي. تكوّن من (136) قائدًا، وُزّعت عليهم الاستبانة، واستُرجعت (120) استبانة صالحة للمعالجة الإحصائية. واستُخدمت استبانة خماسية التدريج تضمنت مقياس GAIUS بأبعاده الثلاثة، ومقياس DAL بأبعاده الأربعة. وحُلّلت البيانات باستخدام برنامجي SmartPLS و SPSS.واختُبرت الفرضية الرئيسية منفصلة عن الفرضيات الفرعية الأربع.

وأظهرت النتائج علاقة إيجابية دالة إحصائيًا بين توظيف الذكاء الاصطناعي التوليدي وكفاءات القيادة الأكاديمية الرقمية، إذ بلغ معامل المسار للفرضية الرئيسية($\beta = 0.842, p < 0.001$) ، بقوة تفسيرية($R^2 = 0.612$) ، وهو أثر كبير. وكان أقوى الأبعاد ارتباطًا الاستشراف الاستراتيجي الرقمي، يليه تنسيق الموارد، ثم الوعي التكنولوجي، بينما جاء بناء الثقافة الأضعف نسبيًا. وتشير النتائج إلى علاقة ارتباطية لا سببية. ويظل التفسير حذرًا.

وتتضمن حدود الدراسة الاقتصار على جامعة واحدة، والاعتماد على التقرير الذاتي، والتصميم المقطعي، وغياب المتغيرات الوسيطة أو المعدلة، وعدم تقييم تحيز عدم الاستجابة. وتوصي الدراسة بتبني استراتيجيات عملية لتعزيز التكامل بين الذكاء الاصطناعي التوليدي والقيادة الرقمية، وبإجراء بحوث طولية ومقارنة. وتفتح آفاقًا بحثية.

الكلمات المفتاحية: الذكاء الاصطناعي التوليدي، القيادات الأكاديمية الرقمية، القيادات الجامعية

The Role of Employing Generative AI in Enhancing the Competencies of Digital Academic Leaders: An Exploratory Study of the Views of a Sample of Academic Leaders at Misan University

Mohammed Raoof Al-Musawi[1] Intisar Abbas Jebur Al-Awidi[2] Mohammed Ahmed Waham[3]

Abstract

This study examines the relationship between the utilization of generative artificial intelligence and digital academic leadership competencies among academic leaders at the University of Maysan in Iraq. It employed a quantitative cross-sectional survey design and utilized a census approach (surveying the entire population) because of the study's small population size. The population consisted of 136 leaders; questionnaires were distributed to them, and 120 valid responses were retrieved for statistical analysis. A five-point Likert scale questionnaire was used, incorporating the GAIUS scale (three dimensions) and the DAL scale (four dimensions). Data were analyzed using Smart PLS and SPSS software. The main hypothesis was tested separately from the four sub-hypotheses.

The results revealed a statistically significant positive relationship between the utilization of generative artificial intelligence and digital academic leadership competencies; the path coefficient for the main hypothesis was $\beta = 0.842$ ($p < 0.001$), with an explanatory power of $R^2 = 0.612$, indicating a substantial effect. The dimension showing the strongest correlation was "digital strategic foresight," followed by "resource coordination" and

"technological awareness," while "culture building" was relatively the weakest. The results indicate a correlational rather than a causal relationship; thus, interpretation requires caution.

The study's limitations include its restriction to a single university, reliance on self-reporting, the cross-sectional design, the absence of mediating or moderating variables, and the lack of an assessment of non-response bias. The study recommends adopting practical strategies to enhance the integration of generative AI and digital leadership, as well as conducting longitudinal and comparative research, thereby opening up new research avenues.
Keywords: Generative artificial intelligence, digital academic leadership, university leadership

Introduction:

Advanced education in the present decade is undergoing a radical alteration driven by the accelerating pace of generative artificial intelligence (AI) technologies. These technologies have reshaped educational and administrative processes, creating a pressing need for the concept of digital academic leadership as a fundamental obligation for university leaders. These leaders can no longer efficiently lead their institutes without a strong strategic vision, advanced technological awareness, and the ability to cultivate innovative organizational cultures. Despite the increasing number of studies on AI needs and digital leadership, most have followed parallel paths., supervising the crucial question: How can the application of generative AI Improve the competencies of digital academic leadership? Systematic reviews have shown that over 78% of the leadership skills required in this epoch are associated to non-technical dimensions, confirming that the impact of AI infuses the very core of leadership competencies, not just technical aspects.

Addressing this gap is becoming increasingly significant given the growing awareness among leaders of these technologies compared with their actual willingness, which remains limited to adopt them. This awareness presents challenges to academic integrity, data privacy, and ethical governance, in addition to placing extra burdens on leaders' digital capabilities. Consequently, bibliometric analyses have identified AI governance and theoretical integration as future priorities in educational leadership research. Therefore, this research aims to bond this gap by examining the impact of employing generative AI on enhancing the digital academic leadership competencies of university leaders. It employs a quantitative methodology and firm theoretical frameworks, relying on previously consistent and validated tools. The study's significance stems from its contribution of a theoretical

framework to an emerging field of knowledge and its provision of practical recommendations for developing leadership agendas and supporting the position of universities in a rapidly changing educational l and scape. This investigation is structured around four m i n sections: the first addresses the methodological framework; the second presents the theoretical framework for the two variables; the third analyzes the data and tests the physical model using PLS-SEM; and the fourth concludes with a discussion of the implications and recommendations.

Research Paragraphs

Section One: Methodological Framework of the Study

First: Research Problem

Higher education institutions in the digital age face mounting challenges in keeping pace with rapid technological advancements, particularly the emergence of Generative Artificial Intelligence (GAI), which has increasingly impacted educational and administrative processes within universities. While GAI offers opportunities to enhance educational practices, administrative workflows, decision-making, and institutional performance, effectively leveraging it requires academic leaders to develop appropriate digital competencies and adapt their leadership practices to the evolving technological landscape.

This issue is of particular significance for Iraqi higher education institutions, including the University of Misan, where the integration of emerging technologies may be hindered by challenges related to technological infrastructure, digital leadership development programs, institutional readiness, and the absence of clear institutional strategies for incorporating AI into academic and administrative practices. Consequently, university leaders face the imperative to strengthen their ability to understand emerging technologies, anticipate future developments, coordinate institutional resources, and foster an organizational culture that supports digital innovation.

At the same time, the concept of "digital academic leadership" has emerged as a crucial framework for understanding the competencies required by university leaders amidst the digital transformation of higher education environments. In the

current study, these competencies are defined across four dimensions: digital strategic foresight, resource coordination, technological awareness, and culture building. Despite growing academic interest in artificial intelligence and digital leadership, empirical research examining the relationship between the use of generative AI and these specific dimensions of digital academic leadership remains limited, particularly within the context of Iraqi higher education.

This research gap aligns with evidence from recent systematic reviews indicating that over 78% of leadership skills relevant to generative AI are associated with non-technical dimensions (Gomes, 2026,p. 156). This finding suggests that the implications of generative AI for leadership extend beyond technical skills to encompass strategic, organizational, adaptive, and human-centric competencies. Consequently, studying the use of generative AI and its relationship with digital academic leadership requires focusing not only on the extent to which university leaders utilize these technologies but also on how such usage relates to the development of broader leadership competencies. Accordingly, the problem addressed by this study lies in the limited empirical understanding regarding the level of generative AI (GAI) usage among academic leaders at Misan University, their level of digital academic leadership competencies, and the nature of the statistical relationship between generative AI usage and these competencies. To address this issue, the study seeks to answer the following research questions:

1. What is the level of Generative AI (GAI) usage among academic leaders at the University of Misan in terms of perceived educational value, current usage patterns, and perceived utility?
2. What is the level of digital academic leadership competencies among academic leaders at the University of Misan across the dimensions of digital strategic foresight, resource coordination, technological awareness, and culture building?
3. Is there a statistically significant relationship between the use of Generative AI and digital academic leadership competencies among academic leaders at the University of Misan?

Second: The Importance of the Study

The importance of this study lies in its two complementary aspects: theoretical and empirical.

First, the theoretical importance (the knowledge aspect): The study's theoretical significance stems from its filling a clear knowledge gap in both Arab and international administrative literature. This gap is characterized by the scarcity of empirical studies that have addressed the relationship between employing generative artificial intelligence (in its three dimensions) and enhancing digital academic leadership competencies (in its four dimensions) in the context of a single educational background. This study responds to the research calls made by several scholars (Jing et al., 2025; Gomes et al., 2026; Deroncele-Acosta et al., 2025) to further investigate the factors influencing the enhancement of digital academic leadership competencies. It does so by presenting a theoretical model that integrates the two study variables in the interior a single analytical outline, thus enriching the body of knowledge and providing a foundation upon which future researchers can shape in diverse academic backgrounds. The study also gains significance from being, to the best of the researchers' knowledge, one of the first studies to address this topic in the Iraqi background, thus causal to enriching Arab scientific research in the field of digital leadership and practical artificial intelligence technologies.

Secondly: Field Significance (Applied Aspect): The field significance stems from its focus on directing the attention of university leaders at the University of misan—the study's location—to the importance of leveraging generative artificial intelligence to improve their leadership performance. It provides them with a practical framework that allows them to overcome the challenges posed by limited infrastructure and weak current digital transformation strategies. The study also offers practical recommendations that contribute to emerging digital leadership programs in the interior the university, cultivating human and technological resource organization mechanisms, and fostering a culture of digital innovation. This will positively influence the quality of academic and administrative outputs, bolster the University of misan competitive position in the evolving educational l and scape,

and assist its decision-makers in captivating well-considered steps toward systematically and sustainably integrating artificial intelligence technologies into in to institutional practices.

Third: Study Objectives

Research aims to determine the level of reproductive artificial intelligence (GI) use across its three dimensions (perceived educational value, current usage patterns, and perceived benefit) amongst the leadership of Misan University.

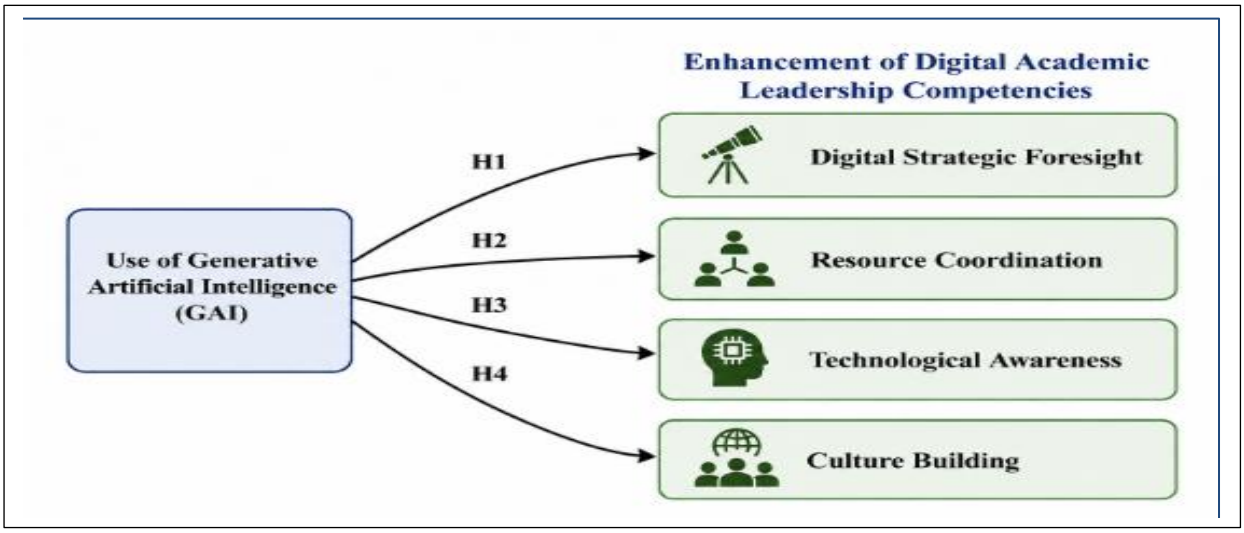
It also aims to measure the level of digital academic leadership competencies across four dimensions (digital strategic foresight, resource coordination, technological awareness, and culture Building) among the University of Misan leaders, from the perspective of the study sample. Furthermore, it aims to examine the relationship between the impact of using generative AI across its three dimensions and enhancing digital academic leadership competencies in the interior the studied environment.

Finally, the study a aims to enrich scientific knowledge by presenting a model that can be used in future studies and to contribute to bridging the existing research gap in Arabic and international administrative literature on the topic of generative AI and digital academic leadership.

Fourth: The hypothetical plan

The study relied on the GAIUS scale issued by Shomotova, Hus AI n, & Elsayary, 2025, with its three dimensions (perceived educational value, current usage patterns, and perceived benefit), to measure the independent variable (digital academic leadership competencies), and on the DAL scale developed by Jing et al. (2025, p. 606) with its four dimensions (digital strategic foresight, resource coordination, technological awareness, and culture Building).

Figure (1) Hypothetical Diagram



Source: Prepared by the researcher

Fifth: Study Hypotheses

Main Hypothesis: There is a statistically significant relationship between the use of generative artificial intelligence (G AI) and the enhancement of digital academic leadership competencies among leaders at Misan University.

(H1): There is a statistically significant relationship between the use of generative artificial intelligence and the enhancement of digital strategic foresight among leaders at Misan University.

(H2): There is a statistically significant relationship between the use of generative artificial intelligence and the enhancement of resource coordination among leaders at Misan University.

.(H3): There is a statistically significant relationship between the use of generative artificial intelligence and the enhancement of technological awareness among leaders at Misan University.

(H4): There is a statistically significant relationship between the use of generative artificial intelligence (G AI) and the enhancement of culture Building among leaders at Misan University.

Sixth: Data Collection and Sample Selection

The study employed a quantitative, cross-sectional survey design to investigate the relationship between the use of Generative Artificial Intelligence (GAI) and digital academic leadership competencies among academic leaders at Misan University. Given the limited size of the study population and the ability to clearly identify and enumerate its members, a census approach was adopted rather than selecting a probability sample. The target population comprised all 136 academic and administrative leaders at Misan University, including the university president and assistants, college deans and their deputies, and heads of academic and administrative departments. Questionnaires were distributed to the entire target

population; 120 valid questionnaires were returned and included in the statistical analysis, representing a response rate of 88.2%.

To assess whether the number of responses obtained was sufficient for the planned Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, an " priori" power analysis was conducted using G*Power 3.1 software. The analysis was based on the assumption of a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and a statistical power of 0.80. The results indicated that the minimum required sample size was 68 observations; thus, the final number of valid responses (120) exceeded the minimum requirement. This analysis served as a supplementary statistical justification for the adequacy of the achieved sample size, rather than a substitute for the study's adopted comprehensive enumeration approach.

Given that 16 distributed questionnaires were either unreturned or unsuitable for analysis, the potential for "non-response bias" was considered. However, the available dataset lacked sufficient information on non-respondents to conduct a direct statistical comparison between them and the respondents. Consequently, the study does not claim to have statistically demonstrated the absence of non-response bias; rather, the relatively high response rate (88.2%) mitigates the likelihood of such bias, even if it does not entirely eliminate it. This limitation was taken into account when interpreting the generalizability of the study's findings.

The questionnaire was designed using a five-point Likert scale. The "Generative AI Usage Scale" (GAIUS) derived from the work of Shumutova, Hussein, and El-Sayed (2025) and the "Digital Academic Leadership Scale" (DAL) derived from the work of Jing et al. (2025) were adapted to suit the higher education environment in Iraq. Prior to the main field administration, the questionnaire underwent review by specialists in management and educational technology to verify content validity and face validity. A pilot study was also conducted, involving approximately 10% of the target study population, to assess the clarity of the items and the time required to complete them, as well as to identify any potential linguistic or procedural difficulties prior to final implementation.

Seventh: Evaluating the measurement Model

The psychometric properties of The Measurement Perfect were evaluated. The convergent validity was tested by the extracted mean variance (AVE) which exceeded the established verge (0.50) . The discriminant validity was verified according to the Fornell-Larcker Criterion and the more recent criterion (HTMT) . Furthermore, the internal consistency was assessed using Cronbach's alpha coefficient and composite reliability (CR), which were all above the acceptable value (0.70). This settles the appropriateness of the collected data for advanced statistical examination and the derivation of objective and solid inferences, which donates to enhancing the reliability of the results and their generalizability in the interior the exact research background (Henseler et al., 2016, pp 1-20).

Section Two: Theoretical Framework of the Study

First: Generative Artificial Intelligence (G AI)

generative artificial intelligence (G AI) is no longer a term that floats around in research circles, but a tangible reality that is reshaping the construction of instructive and administrative organizations in novel manners
. It has transcended its role as a mere tool, becoming a light force that brings about qualitative revolutions in curriculum design, university management, and the subtleties between academic leaders and their subordinates. This pervasive presence has prompted researchers to reconsider their descriptions of the technology and seek conceptual frameworks capable of encompassing its complexities and diverse requests.

Against this background, Runge, Maier, and Rathgeber (2025, p. 1) argue that while the concept of G AI is prevalent in public dissertation, it is rarely precisely defined. So, they propose four essential dimensions for defining it: multimodality, interactivity, flexibility, and productivity. They consider these dimensions a first step toward a definition that transcends the purely technical aspects of the concept. Bianchini (2025, p. 1) agrees with this view, but adds that the definition is still evolving and unstable, especially given the ambiguity surrounding the technical features of these systems, which necessitates non-technical approaches to accurately define them.

meanings focus on the functional essence of the technology. A study published in the Journal of Intelligent Manufacturing (2025, p. 1) labelled generative artificial intelligence as a mechanism that aims to generate new content based on models trained on historical data, whether this content is single-mode or multi-mode, as exemplified by models such as GPT-4. Pahuja, Kukreja, and Singh (2025, p. 2) add another dimension, describing it as capable of generating text, images, and creation suggestions. This aligns with the complete review published in Procedia Computer Science (2025, p. 2), which describes it as a cutting-edge research field demonstrating an exceptional ability to produce innovative content spanning text, audio, and video. The International Journal of Crowd Science (2025, p. 1) also points out that this technology, as a significant branch of artificial intelligence, possesses huge application potential and is having a profound impact crossways various fields.

A education by the Institute of Electrical and Electronics Engineers (IEEE, 2024, p. 1) confirms that generative artificial intelligence (G AI) extends beyond text production to generate creative writing, code, images, videos, and music. This is further supported by a report from the European Information Defense Authority (EDPS, 2024, p 4), which defines the technology as a subset of artificial intelligence that utilizes specialized machine learning models capable of producing a wide and diverse range of content. In the educational background, the International Journal of Teaching (Education Sciences, 2024, p. 172) reproduces the growing interest in this technology, aiming to introduce its fundamental concepts in the field of education. The IEEE Industrial Electronics Magazine (2025, pp. 30-31) summarizes these

insights, stating that G AI signifies a paradigm shift in machine intelligence, moving beyond limited technical applications to broader horizons of accessibility and widespread adoption, with increasing generalizability that allows non-technical users to advantage from it.

In conclusion, this diversity in conceptual insights indicates that generative artificial intelligence is not a static technological marvel, but rather a constantly evolving concept that is shaped according to the background in which it is used, whether educational, research, or administrative, which increases its importance when approached in the interior the framework of digital academic leadership.

The dimensions of paying generative AI in the academic background, as defined by Shomotova, Husain, and Elsayary (2025) in their generative AI use scale (G AI US), can be thorough as follows:

1. Perceived Educational Value

This dimension relates to the mental perception held by academic leaders regarding the developmental return on generative AI in refining academic and administrative performance. This perception extends beyond the technical aspect to the belief that these technologies contribute to improving the quality of outputs, developing teaching methods, enhancing research capabilities, and achieving tangible organizational gains. A study by ElSayary and Hojeij (2026, p. 2) confirmed a positive relationship between this perception and support for responsible AI governance, with a correlation coefficient ($\beta = 0.255$) at a significance level of ($p < 0.001$). This indicates that the perception of educational value is closely linked to the willingness to adopt ethical practices. Field experiments, such as those conducted in flipped classrooms (Integrating lured generative AI into the flipped classroom, 2025, p. 4), have revealed that pupils evaluate the added value of technology based on its contribution to innovation and learning, while still harboring some reservations about its potential to undermine traditional university teaching. This suggests that this perception is the product of a complex interplay between expected benefits and potential concerns.

2. Current Usage Patterns

This dimension ranges from the theoretical to the practical, from the conceptual to the doing. It gages the frequency and extent of university leaders' use of generative AI tools in their daily activities, such as analyzing academic data.
creation intelligences, and developing strategic plans. Shomotova et al. (2025, p. 1) have given this dimension particular position because it reveals the gap between theoretical awareness and practical application. Statistics presented by DeStefano, Hackney, and Moskal (2026, p. 31) obviously settle this gap. While 88% of pupils are familiar with generative AI concepts, only about a neighborhood use these tools in academic exertion.
76% have not received formal instruction on how to use them. This bring into line with the findings of additional study (To adopt or to ban?, 2025, p. 2), which also

found a clear difference between personal and academic use. 69.2% of accused used the technology in personal projects, compared to only 38.7% for academic tasks, suggesting ethical or regulatory barriers that prevent the intention from Being interpreted into practice.

3. Perceived Utility

Even though usage designs reflect the quantity of Communication , perceived utility reproduces its depth and substance. It expresses the degree to which university leaders perceive the practical benefits of employing these technologies to improve their leadership competences. A study by (Shomotova et al. 2025, p. 1) proclaimed that perceived utility is the "strongest predictor of use," connotation that the perception of handy and academic return is the primary driver of receipt and continued use. This conclusion is reinforced by Chiu's (2025, p. 1) study, which links user awareness to perceived utility through status quo bias theory, confirming that user awareness plays a pivotal role in shaping their perception of utility. Research available in the journal "Education and Information Technologies" (2025, p. 2) indicates that university students are highly sensitive to this dimension, and that its direct impact on behavioral intent to use AI overshadows other factors such as perceived ease and enjoyment. This reproduces a clear practical tendency in adopting these technologies in the interior academic settings.

Considering these three dimensions composed, we observe that they form an integrated framework for understanding the dynamics of employing generative aims the academic background: the perceived educational value begins by paving the way for optimistic perception, then the perceived benefit deepens this perception and translates it into a strong motivation to use it, and lastly, current usage patterns determine the actual extent of this application in practice. This integration explains why the G AI US scale has been an effective tool in field studies. It also highlights the importance of understanding each dimension separately to diagnose the strengths and weaknesses of strategies for adopting these technologies, chiefly in backgrounds suffering from gaps between insight and practice, as is the case in Iraqi universities.

Second: Digital Academic Leadership

The concept of leadership in higher education organizations has undergone a remarkable transformation in the last decade due to the hurrying pace of digital transformation and the widespread adoption of digital technologies across various academic and administrative processes. Academic leadership is no longer limited to old-style administrative functions such as planning, organizing, directing, and controlling. Instead, it now encompasses a range of digital and strategic capabilities that enable academic leaders to navigate a complex, constantly evolving, and increasingly technology-dependent university environment.

Recent literature indicates that digital academic leadership rem AI ns a relatively new concept, and studies have yet to establish a unified and comprehensive definition. A systematic review by Cheng et al. (2024) of 39 studies published in

indexed journals revealed that the literature addresses the concept from four main perspectives: the primary views it as the strategic use of digital assets to achieve organizational goals; the second considers it a blend of leadership and digital technology; the third focuses on the attributes and capabilities that a digital leader should possess; and the fourth emphasizes the appropriate use of technology in the various activities of higher education institutions. (Cheng et al., 2024, p. 42).

the perspective of the first approach, digital academic leadership is viewed as the planned use of digital technologies and assets to achieve the organization's goals. This view suggests that technology is not an end in itself, but rather a strategic tool used by the leader to achieve organizational objectives and improve performance. A review by Cheng et al. (2024) shows that this approach is one of the most common definitions in the literature on digital academic leadership. (Cheng et al., 2024, p 41).

The second approach views digital academic leadership as an addition of leadership and technology. That is, the leader not only uses digital tools but also integrates technological capabilities with leadership and problem-solving skills to attained organizational efficiency. The literature has shown that this integration involves uniting human resources with information and Communication technologies, combining traditional methods with digital tools, and Building socio-technological systems capable of achieving organizational goals. (Cheng et al., 2024, p. 41).

The third approach focuses on digital academic leadership as a set of attributes and competencies that a leader should possess in the digital setting. Among these competencies are Building trust, team Building and collaboration, digital Communication , Building virtual teams, social and technological skills, change management, and trustworthiness in the digital environment (Cheng et al., 2024, p. 42).

In the fourth approach, digital academic management is linked to the leader's ability to appropriately use technology in various areas of academic work, including teaching and learning, Communication and collaboration, administration, and research. This means that the essence of digital leadership lies not merely in possessing technical information, but in the ability to select and employ the appropriate technology in a way that aligns with the nature of the task and the institution's objectives (Cheng et al., 2024, p. 41).

another perspective, Ehlers (2020) argues that digital leadership in higher education should be understood in the interior the framework of leading the institution's digital transformation processes, rather than simply as a leader possessing technical services. He highlights that leadership in the digital environment involves a relational process AI med at influencing, coordinating, and constructing meaning to achieve organizational goals. Furthermore, digital transformation in higher education institutions requires Building a cohesive strategy and attractive employees and stakeholders in change processes (Ehlers, 2020, p. 8).

Ehlers (2020) adds that digital transformation in advanced education institutions should be linked to changing organizational culture, structures events, values, and

delay practices, as well as developing participation and Communication structures that help memberships of the institution embrace digital change (Ehlers, 2020, p.10).

From another perspective, Ghamrawi and Tamim (2023) presented a model of digital leadership in higher education based on five dimensions: digital competence, digital culture, digital differentiation, digital governance, and digital support. The study showed that an effective digital leader needs robust technological knowledge and the ability to use it, along with the capacity to build a digital culture based on shared values, cooperation and innovation. (Ghamrawi & Tamim, 2023, p.7090).

The study also showed that a leader's digital competence does not simply mean theoretical knowledge of technology, but rather includes the real ability to use the technologies they seek to disseminate inside the institution. The leader should be a part model in digital practice, not merely a theoretical supporter.

In the same vein, the study demonstrated the importance of digital culture. The success of technological initiatives is linked to leaders' ability to create an academic community whose members share common digital standards, language, beliefs, and attitudes. The study also confirms that a positive and inclusive digital culture helps reduce resistance to change and promotes collaboration, innovation, and continuous learning. (Ghamrawi & Tamim, 2023, p. 7100).

Based on the above, it can that the concept of digital academic leadership encompasses a set of interconnected dimensions; On the one h and , it is the ability to strategically employ technology; on the other h and , it is digital competence that enables the leader to understand and use technology; and on a third h and , it is the ability to lead change and build an organizational culture that supports digital transformation, as well as the ability to coordinate resources and engage stakeholders in the transformation process.

and Accordingly, digital academic leadership can be operationally defined in this study as: the ability of leaders in higher education institutions to employ digital technologies and tools strategically and effectively, anticipate technological developments, coordinate human, financial and technological resources, understand the potential and limitations of technology, and build an organizational culture that supports innovation and digital transformation, in a way that contributes to achieving the academic and administrative goals of the institution and enhances its ability to adapt and perform in the digital environment.

The four dimensions of digital academic leadership, as defined by Jing et al. (2025), can be det AI led as follows:

1. **Digital Strategic Foresight**

Digital strategic foresight refers to the ability of an academic leader to anticipate future trends in technology and digital education, identify potential opportunities and risks, and translate technological developments into strategic visions and plans that bring into line with the institution's objectives.

Cheng et al. (2024) highlighted that a clear technological vision is a fundamental dimension of digital academic leadership, and that this vision is linked

to technological foresight, the implementation of digital strategy, and leading change. The review's findings also indicate that a digital leader needs a clear vision of what the institution should be in the future and the ability to anticipate potential negative penalties associated with technical change. (Cheng et al., 2024, pp. 41–42).

Ehlers (2020) underscores the importance of a shared vision for digital transformation across higher education institutions, as well as the integration of digital transformation concepts into the institution's existing strategies and policies. (Ehlers, 2020, p. 10).

Thus, digital strategic forethought does not simply mean forecasting upcoming technologies, but rather the leader's ability to interpret the digital environment, identify its trends, align it with the institution's mission and objectives, and then interpret this vision into actionable decisions and plans.
Operationally, it is defined as the academic leader's ability to forestall future digital developments, identify associated opportunities and challenges, and develop a vision and strategic plans for leveraging technology in accordance with the university's goals.

2. Resource Coordination

Resource coordination refers to the academic leader's ability to mobilize, allocate, and coordinate human, financial, and technological resources to provision and ensure the sustain nobility of digital transformation projects.

The literature on leadership and digital transformation in higher education emphasizes that implementing digital transformation requires more than just providing technology. It necessitates organizing human resources, emerging employee capabilities, and providing the necessary infrastructure and support for change processes. Ehlers (2020) indicates that implementing digital transformation requires attention to employee professional development, cultivating digital competencies, and providing training and support to grow digital practices in education and administration. (Ehlers, 2020, p. 10).

Recent literature also demonstrates that the relationship between digital leadership and strategic resource allocation has develop increasingly clear in the background of digital transformation. The effectiveness of digital initiatives is linked to the availability of training, support, infrastructure, and the arrangement of capitals with alteration goals. (Deogaonkar, 2025, pp. 1105–1119).

So , within the context of digital academic leadership of digital academic leadership spreads beyond direct financial allocation. It encompasses prioritizing digital initiatives, providing appropriate infrastructure, developing staff capabilities, and directing resources toward initiatives that deliver the greatest academic and institutional value.

Operationally, it is defined as the ability of an academic leader to mobilize, coordinate, and allocate human, monetary, and technological resources and direct them toward digital transformation priorities, ensuring the necessary supplies for implementing and sustaining digital initiatives.

3. Technology Awareness

Technology awareness refers to the level of understanding an academic leader has of modern digital technologies, their functions, capabilities, and risks, and their ability to assess their suitability to the moot and administrative background and make informed decisions regarding their adoption and use.

Cheng et al. (2024) indicate that sing digital awareness is a fundamental measurement of digital academic leadership, and that an effective digital leader needs to understand technology and its capabilities, along with the ability to disseminate digital awareness among staff and members of the academic community. (Cheng et al., 2024, pp. 41–43).

On the other h and, Garawa and Tamim (2023) demonstrate that a leader's digital competence requires applied knowledge of technology and the ability to use it effectively. A leader who leads a technology initiative should possess a high level of expertise in the technology they seek to deploy in the interior the organization. (Ghamrawi & Tamim, 2023, pp. 7098–7099).

So , technological awareness should not be reduced to knowing how to operate digital tools. Rather, it encompasses a leader's ability to understand the potential uses of technology, assess its suitability, weigh its benefits and risks, and make informed decisions about adopting, developing, or continuing to use it.

Operationally, it is defined as the academic leader's aptitude to understand modern digital technologies, their potential, and their challenges; to evaluate their suitability for the university environment; and to make informed choices about their use in academic and administrative processes.

4. Culture Building

Culture Building refers to the academic leader's aptitude to create an structural situation that encourages innovation, digital learning, collaboration, and acceptance of change, and helps members of the university public adopt technology as part of the institution's practices.

Ehlers (2020) emphasizes that digital transformation in higher education institutions must be understood as a profound change in organizational culture, encompassing structures, procedures, rules, values, and practices. Simultaneously, it needs the establishment of appropriate structures for dialogue, participation, and Communication . (Ehlers, 2020, p. 10) Ghamrawi and Tamim (2023) also found that digital leadership requires developing a digital culture based on shared values that support collaboration and novelty, and that Building this culture helps members of the academic community move from resisting digital creativities to accepting and attractive with them. (Ghamrawi & Tamim, 2023, p. 7101).

Cheng et al. (2024) further emphasize that developing digital awareness, Building a digital culture, and fostering teamwork among investors are central elements of operative academic leadership. It is worth noting that institutions need a culture that encourages lifelong learning and the ability to adapt to digital disruption (Cheng et al., 2024, p. 43).

Accordingly, Building a culture signifies the human and social dimension of digital academic leadership, as it transforms technology from mere tools and devices into shared practices, values, and attitudes in the interior the institution.

Operationally, it is defined as the ability of an academic leader to build an organizational environment that encourages digital innovation, collaboration, and lifelong learning; fosters trust, acceptance, and participation in digital transformation initiatives; and helps integrate digital practices into the daily culture of the university institution.

Section Three: Data Analysis and Results Presentation

Quantitative data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS software. The analysis followed a two-stage procedure: first, evaluating the measurement model to verify the reliability and validity of the latent variables (the constructs under study); and second, evaluating the structural model to examine the hypothesized relationships between the use of Generative AI (GAI) and digital academic leadership competencies.

The measurement model evaluation encompassed indicator loadings, Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) to assess indicator reliability, internal consistency, and convergent validity. Discriminant validity was evaluated using the Heterotrait-Monotrait (HTMT) ratio, supplemented by the Fornell-Larcker criterion. Additionally, collinearity among predictor variables was assessed using Variance Inflation Factor (VIF) values.

The structural model was evaluated using standardized path coefficients (β), t-values derived from bootstrapping, p-values, and bias-corrected and accelerated (BCa) confidence intervals. The explanatory power of the endogenous constructs was assessed using the coefficient of determination (R^2), while the effect size of the structural relationships was evaluated using the f^2 coefficient. Predictive relevance was assessed using the Q^2 index, while the model's approximate fit was evaluated using the Standardized Root Mean Square Residual (SRMR) index.

Complementing the assessment of explanatory power, the predictive capability of the structural model was also taken into account. Accordingly, the interpretation of the PLS-SEM results was not limited to the statistical significance of path coefficients but also encompassed the model's explanatory power, effect sizes, multicollinearity indicators, predictive relevance, and model fit indices.

First: Measurement Model Assessment

The measurement model was evaluated to assess the reliability, convergent validity, and discriminant validity of the study constructs. Indicator reliability was assessed using standardized factor loadings, while internal consistency reliability was examined using Cronbach's alpha and composite reliability (CR). Convergent validity was evaluated using the average variance extracted (AVE).

As shown in Table (1), factor loadings were generally satisfactory, with the majority exceeding the recommended threshold of 0.70. The only relatively lower loading was observed for item PUT3 (0.671); this item was retained because the

loading value remained close to the recommended threshold and its removal did not result in a substantial improvement in the reliability or convergent validity of the respective construct. Cronbach's alpha values ranged from 0.778 to 0.845, composite reliability values from 0.855 to 0.893, and AVE values from 0.602 to 0.671. These results indicate satisfactory internal consistency and convergent validity across the study constructs.

Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. The HTMT criterion was examined to determine whether the constructs were empirically distinct from one another; ...while the Fornell-Larcker criterion provides an additional assessment of discriminant validity. Together, these procedures offer a more comprehensive evaluation of the distinctness of the study's components.

Table (1): Factor Loadings, Internal Consistency, and Convergent Validity.

main Variable	Dimensions	Items	Factor Loading	Cronbach's α	(CR)	(AVE)
Generative AI	Perceived Educational Value (PEV)	PEV1	0.781	0.815	0.872	0.628
		PEV2	0.813			
		PEV3	0.794			
		PEV4	0.763			
	Current Usage Patterns (CUP)	CUP1	0.802	0.837	0.888	0.665
		CUP2	0.792			
		CUP3	0.835			
		CUP4	0.761			
	Perceived Utility (PUT)	PUT1	0.756	0.778	0.855	0.602
		PUT2	0.773			
		PUT3	0.671*			
		PUT4	0.782			
Digital Academic Leadership	Digital Strategic Foresight (DSF)	DSF1	0.821	0.845	0.893	0.671
		DSF2	0.793			
		DSF3	0.814			
		DSF4	0.805			
	Resource Coordination (RCO)	RCO1	0.784	0.816	0.870	0.626
		RCO2	0.768			
		RCO3	0.815			
		RCO4	0.797			
	Technology Awareness (TAW)	TAW1	0.805	0.831	0.881	0.651
		TAW2	0.837			
		TAW3	0.778			
		TAW4	0.754			
	Culture Building (CUL)	CUL1	0.792	0.824	0.879	0.643
		CUL2	0.816			
		CUL3	0.769			
		CUL4	0.787			

Source: Prepared by the researcher based on Smart PLS.

Second: Descriptive Statistics of the Studied Constructs.

Table (2) signifies a pivotal diagnostic tool for assessing the reality of digital transformation at the University of misan. It clearly reproduces the significant disparity between levels of cognitive awareness on the one h and , and behavioral

and cultural practices on the other, by monitoring the item averages and st and ard deviations of the dimensions of the two variables: generative artificial intelligence and digital academic leadership. Through careful examination of this data, an accurate diagnosis of the state of university leadership can be drawn.

When examining the generative artificial intelligence variable, the dimension of "perceived educational value" (PEV) st and s out with ~~a~~ general average of 4.01, with item averages reaching between 3.87 and 4.10. This confirms the leadership's firm belief in the transformative capabilities of these technologies in cultivating educational outcomes and supporting scientific research. This signifies a valuable knowledge base that can be built upon in any development strategy and is considered one of the university's primary strengths. This high theoretical awareness suddenly clashes with the "Current Usage Patterns" (CUP) dimension, which recorded the lowest overall average among all dimensions (3.76), and with remarkably low item averages, as the fourth item (concerned with the use of technology in data analysis and strategic decision-making) reached only 3.45. The high standard deviations (which reached 1.15) revealed a stark disparity in practices between colleges and departments, representative a deep gap between "theoretical awareness" and "practical application." Leaders recognize the importance of artificial intelligence but do not use it in their delay tasks, and this is a critical behavioral gap that requires immediate remedial intervention that goes beyond holding awareness seminars to imposing practical usage practices in reports and meetings. Between these two extremes, the Perceived Usefulness (PUT) dimension occupies a middle ground with an average of 3.89., the low average of its third item, at 3.52, reveals that leaders do not perceive a tangible impact of these technologies on their daily personal achievements. This necessitates disseminating local success stories in the interior the university that demonstrate the immediate practical applicability of artificial intelligence in solving real-world administrative problems.

In the background of the digital academic leadership variable, the results reveal a similar contradiction, indicating more complex dimensions. The "Technological Awareness" (TAW) dimension stands out as the strongest strength of the entire study, with an overall average of 4.07. Its second item, related to understanding the capabilities and challenges of modern technologies, recorded the highest average in the table (4.25) with a low standard deviation (0.83), indicating strong consensus. This confirms that the academic leaders in misan are not merely passive users, but highly digitally literate individuals with extensive knowledge of digital tools. This is a tremendous strategic advantage, making it imperative to investiture them in advanced technologies, rather than just basics, and to empower them to trade n their own staff. The "Digital Strategic Foresight" (DSF) dimension comes in second place, with an overall average of 3.96 and item averages ranging from 3.94 to 4.07.

This reproduces the leaders' ability to chart a clear roadmap for the digital future and anticipate technological changes. This insightful vision is a valuable asset that should be utilized by the university's strategic preparation committees. , this lively cognitive l and scape obscures the “Resource Coordination” (RCO) dimension, which came in with an overall average of 3.84, but the low average of its second item to 3.67 reveals the suffering of leaders from a feeling of official helplessness; they have the vision and awareness, but their h and s are tied due to the absence of budgets, human resources, and technical equipment, which calls for intervention from senior management to allocate an independent budget for digital transformation, then the strategies will rem AI n ink on paper. The inconsistency reaches its peak in the "Culture Building " (CUL) dimension, which recorded the lowest overall average among the digital leadership dimensions (3.78). The averages of its individual items were the lowest and most dispersed, with the third item (related to encouraging experimentation with new tools) dropping to 3.50 with a high standard deviation of 1.13. This indicates a resounding failure on the part of leaders to translate their individual awareness and technological knowledge into a vibrant, innovative organizational culture. There are no incentives, rewards, or systems to motivate members to adopt digital practices, and individual knowledge here is stagnant and not disseminated. This signifies the most serious organizational gap in the university.

So , this comprehensive diagnosis reveals that misan University suffers from a severe "dualism crisis": it possesses leaders with open minds, advanced awareness, and a future-oriented vision (as demonstrated in the PEV, TAW, and DSF dimensions), but simultaneously, it is unable to translate this wealth of knowledge into delay practices and a sustainable institutional culture (as demonstrated in the CUP and CUL dimensions), and it lacks adequate material and human support to translate visions into actions (as demonstrated in the RCO). Thus, the remedial recommendations must stem from this accurate diagnosis: First, capitalize on the intellectual and forward-looking strengths by transforming these leaders into digital ambassadors and advanced trainers. Second, address the administrative gaps by allocating clear budgets and deploying tangible, practical applications that demonstrate their effectiveness. Third, and most urgently, surgical intervention in the cultural and behavioral structure is necessary , by explicitly including digital leadership criteria in the yearly performance evaluation of leaders, launching yearly awards for the most innovative colleges, and transforming the irregular and inconsistent use of technology into a comprehensive and Anabel organizational culture. Then, the gap between what the leadership knows and what it actually does

will continue the major obstacle preventing any real digital transformation at Misan University.

Table (2): ***Descriptive Statistics of the Deliberate Variables***

Variable	Dimension	No. of Items	Item Means (M)	Item St and are Deviations (SD)	Dimension Overall Mean
(G AI)	**(PEV)**	4	3.96, 4.10, 3.94, 3.87	0.92, 0.87, 0.95, 0.99	**4.01**
	(CUP)	4	3.60, 3.58, 3.78, 3.45	1.10, 1.07, 1.01, 1.15	**3.76**
	(PUT)	4	3.87, 3.93, 3.52, 3.94	0.98, 0.93, 1.14, 0.94	**3.89**
(DAL)	**(DSF)**	4	4.07, 3.94, 4.05, 3.95	0.88, 0.95, 0.87, 0.96	**3.96**
	(RCO)	4	3.77, 3.67, 3.87, 3.81	1.04, 1.09, 0.98, 1.02	**3.84**
	(TAW)	4	4.19, 4.25, 4.01, 3.97	0.85, 0.83, 0.94, 0.96	**4.07**
	(CUL)	4	3.62, 3.70, 3.50, 3.63	1.10, 1.06, 1.13, 1.09	**3.78**

Source: Prepared by the researcher using SPSS software.

Third: Hypotheses Testing and Path Coefficient Significance Analysis

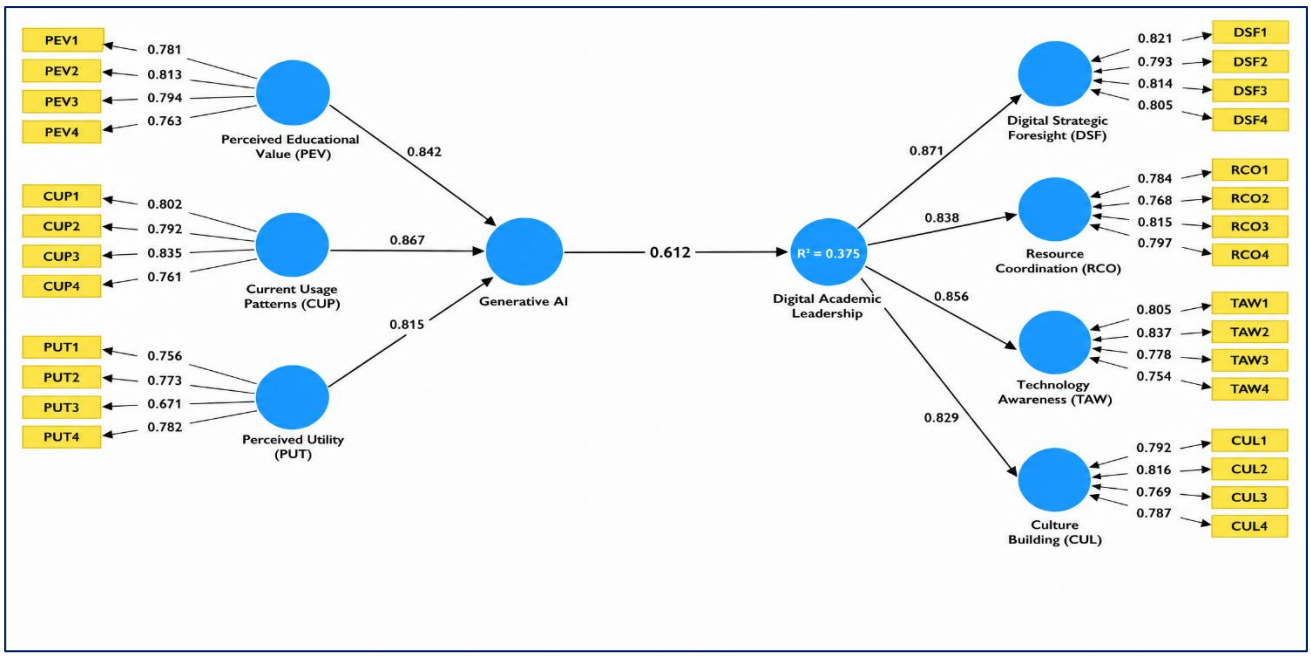
To scrupulously measure the meaning of the hypothesized causal relations in the interior the structural model, a non-parametric bootstrapping procedure was employed, utilizing 5,000 resamples with bias-corrected and accelerated (BCa) sureness intervals. This approach, recommended by (Sarstedt et al. 2017, p 625), effectively alleviates defilements of ordinariness molds and yields robust st and ard errors, t-statistics, and p-values for all assessed path constants.

Significance was strongminded using a two-tailed t-test, where values more than 1.96, 2.58, and 3.29 were deemed significant at the 0.05, 0.01, and 0.001 levels, respectively (Hair et al., 2017, pp. 1–363).

Assumed the scale of the path coefficients derived from the organizational model, this study assumed the 0.001 significance verge as the m AI n criterion for hypothesis receipt.

Table (3) presents the testing consequences for the four sub-hypotheses (H1–H4), alongside the overarching main hypothesis, linking each dimension of digital academic leadership capabilities (as a second-order dependent construct) to generative AI operation (as both a mediating and independent construct). All hypothesized paths established statistical meaning at the chief level.

Figure (2): Variable Path Model



Source: Smart PLS program outputs.

Table (3): Hypotheses Testing Results

Hypothesis	Causal Path	(β)	(M)	(STDEV)	T	P	BCa 95% CI	Decision
Main	G AI → DAL Competencies (Overall)	0.842*	0.840	0.032	26.31	0.001	[0.779, 0.898]	Supported
H1	G AI → (DSF)	0.871	0.868	0.029	30.03	0.001	[0.814, 0.920]	Supported
H2	G AI → (RCO)	0.838	0.835	0.036	23.28	0.001	[0.768, 0.894]	Supported
H3	G AI → (TAW)	0.829	0.825	0.037	22.41	0.001	[0.759, 0.886]	Supported
H4	G AI → (CUL)	0.792	0.788	0.045	17.60	< 0.001	[0.704, 0.862]	Supported

Source: Prepared by the researcher based on Smart PLS.

The results fully support the main hypothesis and the four sub-hypotheses. Path coefficients (β) ranged from 0.792 to 0.871, and all were statistically significant at the $p < 0.001$ level. Specifically, the β coefficient for the path from GAI to comprehensive digital academic leadership competencies was 0.842 ($T = 26.31$, $p < 0.001$); to digital strategic foresight (DSF), 0.871 ($T = 30.03$, $p < 0.001$); to resource coordination, 0.838 ($T = 23.28$, $p < 0.001$); to technological awareness, 0.829 ($T = 22.41$, $p < 0.001$); and to culture building, 0.792 ($T = 17.60$, $p < 0.001$).

It is important to note that the β coefficient reflects the strength and direction of the relationship and should not be interpreted as "effect size." In the PLS-SEM model, effect size is assessed using Cohen's f^2 metric, where values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Hair et al., 2019). Based on the available R^2 values, the f^2 value for the main path (GAI → DAL competencies) was 1.577, while for the DSF path (i.e., GAI → DSF) it was 0.600; both figures indicate a large effect size. Regarding the remaining dimensions (RCO, TAW, and CUL), it was not possible to calculate the f^2 value because their R^2 values were not included in the original output. Furthermore, data on predictive relevance (Q^2) were unavailable in the original output and are therefore not reported here. Consequently, there is a strong positive relationship between the use of Generative AI and the Digital Academic Leadership competencies of leaders at Misan University, with the strongest path observed in relation to Digital Strategic Foresight.

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The Resource Coordination (RCO) pathway ranked second in strength (β = 0.838; $T = 23.28$; $p < 0.001$). This result suggests that generative AI technologies enhance the allocation of human, financial, and technological resources necessary to support digital transformation. However, the R^2 value for this dimension was not reported in the original output, and therefore the f^2 value could not be computed for this path.

the Technology Awareness (TAW) pathway recognized a significant impact (β = 0.829; $T = 22.41$), underscoring the role of AI in ornamental leaders' technical

competence and their knowledge of emerging digital tools. Temporarily, the Culture Building (CUL) pathway achieved the lowest coefficient, but it rem aimed considerable and statistically significant (β = 0.792; T = 17.60), suggesting that while AI effectively contributes to fostering a culture of novelty and digital transformation, This specific outcome may require extra organizational creativities and human-centered efforts to fully realize its possible.

Also the 95% confidence intervals intended using the BCa model for all tray ls do not comprise zero, which strongly reinforces The statistical meaning of these relations and eliminates any negative or spurious effects. It is also distinguished that the trail coefficient for the fundamental hypothesis (0.842) is a biased estimate of the overall result of AI on the combined concept of digital leadership. This aggregate value, derived from the four-dimensional effects, lends empirical trustworthiness to the theoretic hypothesis that the transformative control of generative AI is most marked in the areas of strategic and conscious leadership, while remaining consistently effective albeit relatively less so In national and legislative features.

Table (4): Path Coefficients, Effect Size (f^2), and Explanatory Power (R^2)

Path	β	T	p	R^2	f^2	Effect Size
GAI → DAL Competencies (Overall)	0.842	26.31	< 0.001	0.612	1.577	Large
GAI → DSF	0.871	30.03	< 0.001	0.375	0.600	Large
GAI → RCO	0.838	23.28	< 0.001	Not reported	Not computable	—
GAI → TAW	0.829	22.41	< 0.001	Not reported	Not computable	—
GAI → CUL	0.792	17.60	< 0.001	Not reported	Not computable	—

Source: Prepared by the researcher based on Smart PLS.

Discussion of Results

The main objective of this study centered on decisive the causal relationship between the assignment of generative artificial intelligence (GAI) across its three dimensions: apparent educational value, current usage designs, and perceived utility and the enhancement of digital academic leadership capabilities including digital strategic . resource organization, technology awareness, and culture Building among the leaders of the University of Misan. The study further required to examine the degree to which these dimensions contribute to explaining the variance in digital leadership performs within the university background.

The analysis indicates that the use of generative AI is positively and significantly associated with digital academic leadership competencies across all four dimensions. However, the cross-sectional design of this study does not permit causal inferences; the findings should be interpreted as evidence of association rather than causation. The discussion below examines possible institutional explanations for the observed variation in the strength of these associations.

The strongest association was observed between generative AI use and digital strategic foresight ($\beta = 0.871$; $T = 30.03$; $p < 0.001$; $R^2 = 0.375$; $f^2 = 0.600$). This may be explained by the nature of strategic foresight as a cognitive and planning-oriented competency, which aligns with the analytical and generative capabilities of AI tools. University leaders who use generative AI may find it particularly useful for scenario planning, trend analysis, and strategic document drafting. However, this interpretation remains tentative and requires further qualitative investigation.

The association with resource coordination was also strong ($\beta = 0.838$; $T = 23.28$; $p < 0.001$), though the R^2 and f^2 values for this dimension were not available in the original output. A possible institutional explanation is that generative AI may assist leaders in drafting budget justifications, mapping resource allocation scenarios, and preparing administrative reports. However, the absence of R^2 and f^2 values limits the ability to assess the explanatory and predictive power of this specific path.

The association with technological awareness was statistically significant ($\beta = 0.829$; $T = 22.41$; $p < 0.001$), but again without available R^2 or f^2 values. This finding is consistent with the possibility that repeated use of AI tools may enhance leaders' familiarity with digital applications. However, the cross-sectional design cannot determine whether awareness precedes or follows use.

The weakest association among the four dimensions was with culture building ($\beta = 0.792$; $T = 17.60$; $p < 0.001$), though it remained statistically significant. This relative weakness may be attributed to the deeply social, gradual, and interactive nature of organizational culture, which is unlikely to be transformed through individual technology use alone. Institutional factors such as incentive systems, evaluation criteria, and collective participation mechanisms may play a more substantial role than individual AI use in shaping organizational culture. This interpretation aligns with the findings of Ghamrawi and Tamim (2023), who emphasized that building a digital culture requires shared values, collaboration, and institutional support structures that extend beyond individual technological competence.

It is important to note that the comparison with prior studies is constrained by the limited availability of empirical research examining the same variables within similar higher education contexts. Several of the studies cited (e.g., Jing et al., 2025; Shomotova et al., 2025) were conducted in different institutional and cultural settings, and their findings may not be directly comparable. Therefore, the comparisons presented here are tentative and should be interpreted with caution.

However, the results revealed substantial variation in the magnitude of the path coefficients depending on each leadership dimension. Specifically, the strongest path coefficient was directed toward Digital Strategic Foresight (DSF), with $\beta = 0.871$, $T = 30.03$, $p < 0.001$. This finding indicates that preparing university leaders with

generative AI tools significantly enhances their capacity to anticipate the future of digital education, strategically plan for rapid technological shifts, and identify emerging opportunities and challenges within the evolving academic landscape. This result aligns with the conclusions of Jing et al. (2025), who affirmed that strategic foresight constitutes the leadership dimension most deeply influenced by digital transformation, as well as with the work of (Alam et al. ,2025, pp 1-31), which highlighted that digital leadership is closely linked to strategic visioning and structural agility. Furthermore, the coefficient of determination for this dimension was $R^2 = 0.375$, meaning that 37.5% of the variance in digital strategic foresight is explained by generative AI use. The f^2 value for this path was 0.600, indicating a large effect size. This underscores the capacity of generative AI to influence future-oriented institutional visions.

Position additional in terms of effect magnitude, the Resource Coordination (RCO) dimension yielded a path coefficient of ($\beta = 0.838$, $P < 0.001$). This effect suggests that leveraging generative AI significantly strengthens leaders' ability to optimally allocate human, technical, and economic resources in support of Digital transformation initiatives. This is reliable with the assertions of (Benitez et al. ,2022, p 8) regarding the pivotal role of real resource coordination as a core output of digital leadership. It further reproduces the volume of generative technologies to mechanize wants analysis processes and task delivery, thereby redemptive cream of the crop to concentrate on broader strategic priorities.

regarding Technology Awareness (TAW), this dimension also established a robust and substantial effect, with a path constant of ($\beta = 0.829$, $P < 0.001$). This finding strongly corroborates that active engagement with generative AI tools tangibly elevates leaders' technical skill and their familiarity with wounding benefit digital applications in the interior the academic background. This consequence is entirely corresponding with the systematic review conducted by (Deroncele Acosta et al. 2025,p 6), which identified technology awareness and digital literacy as essential transversal competencies intrinsically linked to AI integration cutting-edge higher education. It further proposes that repeated, h and 's happening use of these technologies nurtures self-directed learning among leaders, cumulatively reinforcing their digital skill sets.

The Culture Building (CUL) Recorded the lowest path coefficient among the four dimensions; nevertheless, it rem . robust, substantial, and statistically Significant ($\beta = 0.792$, $P . < 0.001$). Although this positive direction is encouraging, the relatively lower magnitude signals that the influence of generative AI on embedding a culture of innovation and digital transformation in the interior the institution, while important, rem AI ns comparatively less marked than its impact on strategic and cognitive , This relative weakness may be attributed to the inherently complex, socio human nature of culture structure, which is a gradual, interactive process requiring prolonged effort and multifaceted interventions that spread far beyond the mere availability of technological tools.

Calming an enduring official culture necessitates concurrent leadership initiatives such as development dialogic engagement, incentivizing imaginative practices, and redesigning ling behavioral norms elements that technology alone cannot

instantaneously transform. This result partially resonates with the findings of (Myszak and Filina Dawidowicz ,2025,p 12), who suggested that leaders' abilities in the AI era require technological adoption capabilities, yet approved that interpreting such getting into a deeply fixed institutional cultured and integration with incentive systems and participative supremacy instruments.

Rotating to the mediating variable reproductive AI as an overarching construct the results

demonstrated that its three constituent dimensions (perceived educational value, present usage patterns, and perceived utility) together accounted for approximately 61.2% of its total variance. This is a markedly large effect, substantially exceeding Cohen's (1988) threshold for a large result size (0.26), thereby settling that leaders' insights of educational value, their perceived practical benefits, and their actual usage behaviors are main determinants of G AI adoption in the interior the academic environment.

Professed Educational Value (PEV) emerged as the most influential dimension driving G AI adoption, followed closely by current usage patterns and perceived utility. This ladder indicates that cognitive academic motivation supersedes purely instrumental drivers in university backgrounds a finding that, though partially reliable with Shomotova, Hus AI n, and Elsayary (2025), who identified "perceived utility as the strongest predictor of use," reveals a distinctive backgroundual shade. In the Iraqi moot setting, educational value precedence, underscoring the particular emphasis that university leaders place on educational and developing outcomes over mere operational efficiency.

Collectively, these findings underline that Digital Strategic Foresight signifies the leadership competency most powerfully leveraged through the deployment of generative AI in enhancing digital academic leadership at the University of Misan, followed by reserve coordination competences and technology awareness. In difference, Culture Building , despite its clear and positive influence, did not reach the expected impact relative to the additional dimensions. This gap necessitates that university leadership adopt whole, combined strategies that synergistically combine technological enablement with targeted human and organizational interferences. Such an approach is essential to ensure that technological advancements translate into a deeply rooted, institutional ethos, ultimately fostering a complete digital leadership environment characterized by capability… innovation, and active participation across all structural levels.

Study Limitations

Several limitations should be considered when interpreting the findings of this study.

First, the data were collected from only one university, the University of Misan. This restricts how far the results can be generalized to other Iraqi universities or to higher education institutions in different settings. Institutional factors such as size, infrastructure, administrative support, and organizational culture may all influence the relationships examined here.

Second: the study depended on self-reported questionnaire data. This creates a risk of social desirability bias, as respondents may have overstated their use of generative

AI or their leadership competencies because of perceived expectations. The study also lacked objective measures of AI use and independent assessments of leadership competencies.

Third: the cross-sectional design does not allow causal conclusions. The associations observed between generative AI use and digital academic leadership competencies should therefore be understood as correlational, not causal. Longitudinal research is needed to clarify the direction of these relationships and whether they remain stable over time.

Fourth: the study did not include mediating or moderating variables that may affect the relationship between generative AI use and digital academic leadership competencies. Factors such as organizational trust, readiness for change, administrative support, and individual digital self-efficacy may play important roles in shaping this relationship, but they were not examined in the present study.

Fifth: predictive relevance (Q^2) and effect sizes (f^2) could not be assessed for all paths because R^2 values were unavailable for three of the four sub-dimensions (RCO, TAW, and CUL). This limits the ability to fully evaluate the practical significance and predictive power of the structural model.

Sixth: the study used a census approach rather than probability sampling. Although this is appropriate given the small population size, it may introduce selection bias if non-respondents differ systematically from respondents. Despite the high response rate (88.2%), non-response bias could not be statistically assessed because information on non-respondents was not available.

Conclusions

Based on the study's objectives and the statistical consequences derived from the structural model analysis, and without delving into a debt AI led discussion of the answers, the following key conclusions can be drawn:

1. The gap between the high apparent value of education and the modest level of real usage patterns reproduces a severe translation crisis at the University of misan. Theoretic consciousness remains confined to individual perception without being translated into daily practice, highlighting the absence of motivational and institutional devices to transform intention into palpable behavior.
2. lack of correspondence in the impact of planned foresight versus culture structure demonstrates that leaders tend to order long-term planning at the expense of the proactive effort compulsory to build an organizational environment conducive to innovation. This reproduces an imbalance in the distribution of leadership efforts between strategic planning and cultural growth.
3. The incomplete level of quantitative clarification offered by the model indicates that development digital leadership is a complex and multi-layered phenomenon, influenced by factors outside mere technological enablement. It involves the interaction of incentive schemes, moral climate, organizational structure, and the

degree of official readiness, thus necessitating more comprehensive explanatory models.

4. The gap between a high level of technical awareness and a low level of culture Building reproduces the fact that leaders possessing progressive individual digital skills does not promise comprehensive institutional transformation. Personal knowledge rem AI ns imperfect in its impact unless supported by organizational structures and collective mechanisms to expand the scope of influence and engage all sponsors in the alteration process.
5. knowledge over applied contributory motivation discloses a specific backgroundual distinguishing of Iraqi universities. Leaders view artificial intelligence primarily as a academic tool, presenting a strategic opportunity to steer development programs toward academic and research applications first, aligning with their central incentives.
6. low position of culture Building in terms of impact, joined with the variation in practices across colleges, underscores that Building an official digital culture is a complex and long-term social process. It requires open discourse lively participation, and a shift from an individualistic guidance model to an institutional motivational model based on incentives, assessment, and collective appointment.

Recommendations

Part One: Practical Recommendations for University Leadership

The following recommendations follow directly from the study's findings and are addressed to university leaders and decision-makers.

1. **Put generative AI to work in administrative tasks.** The descriptive results reveal a clear mismatch: leaders value generative AI for education, yet actual use remains limited. The university should therefore move beyond awareness seminars and offer concrete, hands-on applications for routine administrative work—report writing, data analysis, and strategic planning, for example.
2. **Create a dedicated budget for digital transformation.** Resource coordination received a low mean score (M = 3.84; item 2 = 3.67), suggesting that leaders feel financial and technical support is inadequate. A clearly allocated budget for digital infrastructure and training would help turn strategic visions into everyday practice.
3. **Include digital leadership criteria in annual performance evaluations.** The weak link between generative AI use and culture building ($\beta = 0.792$) suggests that awareness alone does not change organizational culture. Adding digital leadership indicators to performance evaluations would give leaders institutional incentives to adopt and promote digital practices.

4. **Introduce annual awards for the most innovative colleges.** Culture building also scored low (M = 3.78; item 3 = 3.50). Recognizing and rewarding colleges that integrate digital practices successfully would encourage a culture of innovation and experimentation.
5. **Design training that starts with educational and research applications.** Descriptive statistics indicate that leaders see the greatest value in the educational dimension of generative AI (PEV: M = 4.01). Training should therefore begin with pedagogical and research uses, then gradually move into administrative areas. This approach would align with leaders' existing motivations and beliefs.
6. **Form digital advisory boards in each college.** Practices vary across colleges, as the high standard deviations in the CUP dimension (SD up to 1.15) show. Each college should have its own advisory board to help spread best practices and provide technical guidance.

Part Two: Proposals for Future Research

These proposals are directed to the research community and emerge from the limitations and gaps identified in this study.

1. **Conduct exploratory qualitative research using in-depth interviews and discourse analysis.** Such work could clarify how leaders and subordinates perceive generative AI's effect on cultural and interactive practices within the university, and why its association with culture building appears relatively weak.
2. **Design a longitudinal study over two to three years.** This would track how the relationship between generative AI and digital leadership competencies evolves, and whether these relationships remain sustainable or change over time especially in cultural areas that take longer to develop.
3. **Carry out comparative research between Misan University and other Iraqi universities, both public and private.** This would test the generalizability of the current model and examine contextual influences such as university size, infrastructure, and administrative support.
4. **Test mediating and moderating variables.** Variables such as organizational trust, readiness for change, administrative support, and digital self-efficacy may affect the relationship between generative AI use and digital leadership competencies.
5. **Replicate the study with objective measures of generative AI use** (e.g., system logs or usage analytics) **and independent assessments of leadership competencies.** This would reduce dependence on self-reported data.

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