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Exploring Organisational Drivers and Innovation Attributes of Artificial Intelligence Adoption in Higher Education

Waleed Mugahed Al-Rahmi

Department of Management Information System, College of Business Administration, Dar Al Uloom University, Riyadh 13314, Al Falah, Kingdom of Saudi Arabia. Corresponding Email: waleed.alrahmi@dau.edu.sa

Abstract

This study examines the organisational and technological determinants influencing the adoption of artificial intelligence (AI) technologies specifically data-driven decision support systems (DSS) and smart learning platforms in Saudi Arabian higher education institutions. Guided by the integrated Technology–Organisation–Environment (TOE) framework and Diffusion of Innovations (DOI) theory, the study employs a quantitative approach using a structured survey administered to 300 academic and administrative staff across multiple institutions. The survey captures key constructs, including social trends, organisational culture, sustainability practices, waste management, technology compatibility, relative advantage, complexity, social drivers, innovation attributes, intention to use data-driven DSS, and government regulatory support. Structural equation modelling (SEM) was applied to test the hypothesised relationships and evaluate the interplay among organisational, technological, and environmental factors. The results reveal that internal organisational conditions, particularly organisational culture, sustainability policies, and waste-management practices- significantly strengthen internal social drivers that promote technological change. Technological characteristics, including Compatibility with existing systems and perceived relative advantage, strongly enhance the perceived innovation attributes of AI technologies. These innovation attributes, in turn, serve as a major catalyst for both the intention to use and actual adoption of AI-enabled systems. Adoption within the higher education context was associated with improvements in teaching practices, enhanced learner engagement, and curriculum innovation. Moreover, government regulations and policy incentives emerged as crucial external enablers that facilitate institutional readiness and adoption. This study contributes to the growing body of knowledge on AI integration in higher education by providing an empirically validated model that highlights the interaction between organisational drivers, innovation characteristics, and environmental enablers. The findings offer practical insights for policymakers, higher education leaders, and system designers seeking to accelerate responsible and effective AI adoption in academic environments.

Keywords

Artificial intelligence, structural equation model, technology-organisational framework, diffusion of innovation.

Introduction

Recent years have seen the fast growth of advanced intelligent systems, turning artificial intelligence (AI) from a concept of the future to a present-day enabler of innovation in both organisation and education (Almogren et al., 2024; Dahri et al., 2024). AI systems can process large amounts of data and identify complex patterns. In addition, AI supports the ability to make decisions based on evidence. Thanks to these benefits, AI is starting to become a huge development in various fields like health care (Jagatheesaperumal et al., 2021), finance (Veile et al., 2022), manufacturing (Soomro et al., 2024), and education (Almogren et al., 2024; Dahri et al., 2024). AI-supported management information systems (MIS) are increasingly used in higher education to inform teaching and learning decisions, manage resources and support new kinds of digital pedagogy. MIS infrastructures have been noticed by Liu et al. (2023) to be the backbone of intelligent technologies for strategic alignment and improved competitiveness of the institution during digital transformation. It is important for institutions to better understand the drivers of AI adoption in these systems when looking to enhance operational and pedagogical innovation (Dahri et al., 2024; Dwivedi et al., 2021).

Higher education institutions (HEIs) are interested in the adoption of AIs because of the rapid digital re-engineering of the teaching-learning process and administrative functions. With learning analytics, personalised or adaptive learning platforms, automated feedback tools, and virtual assistants, intelligent technologies are increasingly influencing ways in which instructors design curriculum, engage students and assess performance. Artificial Intelligence Technologies allow organisations to optimise processes and improve accuracy, supporting innovation. According to Jovanovic et al. (2022) and Neiroukh et al. (2024), it includes natural language processing, machine learning, robotics and predictive analytics. In education, these capabilities lead to personalised learning paths, data-driven teaching strategies, and prompt interventions to help students. Predictive systems enable institutions to flag at-risk learners, streamline course design, and facilitate student success (Shah & Wiese, 2018). On the other hand, chatbots (Hopkins et al., 2023; Rudolph et al., 2023), virtual assistants (Pandey & Rai, 2023), and automated academic services (Tian et al., 2024) are helping students in their learning environments by providing them with instant academic, administrative, and other services. The widespread adoption of AI in higher education remains difficult despite these benefits. According to Olan et al. (2022), changes in the culture, infrastructure, processes, and staff capabilities are indispensable. Educational institutions must not only invest in technologies but also in the capacity-building of educators who must learn to integrate AI tools into the curriculum, assessment, pedagogy and other educational functions. The use of AI systems is further complicated by worries about data governance, ethical AI uses, and algorithmic bias and academic integrity as well as disruption to the workforce (Dahri, Yahaya, & Al-Rahmi, 2024). In any learning situation, these problems will raise questions about the role of the teacher, the assessment, and student independence. So, it becomes essential to understand the organisational drivers of AI adoption that can enable institutions to achieve pedagogical innovation ethically and academically (Dahri, Al-Rahmi, et al., 2025).

AI tools in classroom instruction can help automate repetitive teaching activities, offer insights to assist in decision-making, and enhance a teacher's focus on more high-level teaching activities (Cubric, 2020). Neuman (2016) shows that a system is able to analyse large and complex educational data sets. These will help reveal patterns that can help in curriculum redesign. Along with this, it also helps in finding instructional strategies and student support interventions.

Therefore, AI adoption in higher education is on the rise, but it heavily depends on institutional readiness, innovation characteristics, and support environments. Research regarding adoption in the business and healthcare segments is established. However, the higher education context specifically, adoption research on AI influence on teaching quality, curriculum innovation, student engagement and learning outcomes has not been done yet. AI will not only help companies get operational efficiencies and new business models, but it will also allow educators to innovate educationally (Dahri, Dahri, et al., 2025; Dahri, Yahaya, Al-Rahmi, Aldraiweesh, et al., 2024).

Artificial intelligence solutions, such as recommendation engines that take data about students' choices and preferences into account to present content, web-based adaptive tutoring systems and intelligent feedback tools support customised learning experiences that enhance student engagement and academic performance Al-Rahmi et al. (2023) and Singh et al. (2022). According to the study by Olan et al. (2022), smart diagnostic systems and simulation-based learning environments enrich training quality and improve learner outcomes in health and clinical education. Consequently, AI adoption in higher education is not only a technical upgrade. Above all, it is a pedagogical shift that can reconfigure instructional practices, craft data-driven learning cultures, and provide fewer hindrances to innovation.

There are still gaps in the literature despite increasing attention. Previous research studies have emphasised algorithm/technological performance or administrative functionality studies, mostly overlooking the pedagogical and organisational contexts in which AI is embedded in universities. A range of studies is available on the benefits of AI technologies (Cubric, 2020; Olan et al., 2022; Opoku & Fortune, 2013). But there aren't many studies that talk about adoption barriers. Some of these barriers include the reluctance of faculty, low digital capabilities, ethical issues and the complexity of integrating AI in the curriculum and assessment. Moreover, prior studies have focused mainly on developed countries, while the adoption processes in emerging regions have received limited scholarly attention. However, there are marked differences in culture, policy and resources, which could shape the adoption processes differently.

The application of TAM and UTAUT was applied widely to study acceptance of technology at the individual level (Tawafak et al., 2023; Venkatesh et al., 2003). Nevertheless, the models fail to encompass the organisational-level factors for the AI adoption in educational institutions. On the other hand, the TOE and DOI offer comprehensive overviews of institutional readiness, organisational culture, policy environment, and the attributes of the innovation, including Compatibility, complexity, and relative advantage. Combining these frameworks helps to understand how the adoption of AI takes place in HEIs in stages. According to Alsheibani et al. (2020) and Nguyen et al. (2022), it is important for institutions to first assess the Compatibility of AI technologies with educational objectives. This assessment involves considering factors such as perceived usefulness, ease of use, and institutional readiness. (Davis, 1989). Thus, academic leaders must invest in technological infrastructure, substantial faculty development, digital literacy and change management to support change. External forces include government policy, sustainability requirements, industry standards, and global competition, all exert pressures on adoption. It is significant to recognise how these internal and external factors work mutually to enhance the AI-supported teaching and learning practices in universities. In order to address these gaps, this study seeks to identify the factors that influence the adoption of AI in the higher education institutions in Saudi Arabia. It is an exploring context which is rapidly transforming technologically but has empirical coverage limits. The impact of organizational culture,

sustainability practices, social drivers, technological attributes and regulatory pressures on the adoption of AI-enabled decision-support systems and learning tools is investigated. The present study endeavours to offer a holistic perspective on the dynamics of adoption by integrating the TOE and DOI frameworks while also shedding important insights as to how AI-powered innovations can enhance the quality of teaching, curriculum development, learning engagement, and institutional performance.

Literature

The use of next generation digital technologies in higher education institutions is a complex phenomenon that is shaped by forces of technology, organisations and environment. The early aspects of digitisation saw tech adoption largely an engineering issue. Contemporary adoption of intelligent systems, however, necessitates deeper alignment with institutional strategy, academic culture, and teaching–learning priorities. According to Chandra & Kumar (2018), the modern adoption process considers various factors other than technical feasibility, such as strategic coherence, cultural readiness and external pressures (regulatory, competitive and social). In the field of higher education, the meaning of adoption now extends beyond a simple act. Knowledge of these layers can significantly shape pedagogy, assessment, curriculum and overall learning environments.

Several theories have been produced to analyse technological adoption at different levels. The Theory of Reasoned Action TRA is an early model that states the person's behaviour is determined by his attitudes and social norms (Fishbein & Ajzen, 1977). To explain behaviour, TPB was expanded to include perceived behavioral control as an additional predictor of intention (So et al., 2012). Based on these, Davis' (1989) Technology Acceptance Model (TAM) suggested that perceived usefulness and perceived ease of use are the primary determinants of technology acceptance. Research studies involving the application of technology acceptance model (TAM) and its extensions have been popular in education (Venkatesh & Davis, 2000). For example, it has been used to study student and teacher acceptance of AI-powered learning tools, learning management systems, chatbots and virtual learning environments. Yet, such theories predict at an individual level. In higher education institutions, adoption decisions are complicated. They involve multiple actors, policy constraints, strategic considerations, and institutional readiness. However, only partial explanations are offered. To get an organisation to accept the adoption of AI technology, it requires a broader framework that would be able to incorporate the technical, organizational and environmental forces. The broader framework requires that the TOE and DOI framework which makes the suitable framework to on AI adoption in the case of universities.

The three interconnected dimensions of technology, organization, and environment are all connected to one another in the TOE framework (Tornatzky & Fleischer, 1990). Organizations see this framework as a whole. The technology context is concerned with the characteristics of the innovation. Compatibility, relative advantage and complexity are constructs consistent with DOI (Rogers Everett, 1995). Compatibility basically refers to the fit of a technology to already existing practices used in teaching, digital capability and curricular structures (Chatterjee et al., 2021; Pumplun et al., 2019). The seamless Compatibility of AI tools and apps with the platform used by colleges to conduct classes will bring speedier adoption at campuses. Relative advantage relates to the perceived benefits of AI as compared to existing ways of teaching and institutional administration (Gutierrez et al., 2015). Techniques such as AI-powered analytics, adaptive

learning systems, and intelligent tutoring systems are advanced due to the ability of education technologies to offer personalized learning paths. It offers government teachers tanks for early identification of at-risk students. It also helps to make data-informed pedagogical decisions.

Complexity is defined by Rogers (1985) as the perceived difficulty of using or implementing a technology. If AI design is too complicated, academic staff may not take it up because they may not have the confidence, training, or digital skills to use AI. Even though it is said that artificial intelligence systems have immense potential, the learning curve can be a major barrier in the education sector.

The organisational context comprises internal traits that affect how technologies are adopted. These traits consist of structure, culture, leadership and resources (Chandra & Kumar, 2018; Gutierrez et al., 2015). Organizational culture is especially influential. Universities that encourage innovation, cooperation, and experimentation are the ones most likely to adopt and sustain AI-supported teaching and learning. On the other hand, cultures resistant to change or over-bureaucratisation may prevent adoption, even when the technology can do it. The shift towards digital transformation is one of the social trends that impacts the readiness of organisations for AI (Aboelmaged, 2014). Higher education institutions are under increasing pressure to modernise pedagogy, diversify learning modalities and provide data-informed academic assistance. Concerns about sustainability further affect adoption decisions. Universities are increasingly picking technologies that foster long-term economic, social, environmental, and institutional sustainability. Resource availability is another critical factor. AI needs people, infrastructure, cybersecurity, and continuous training to move forward. Educational institutions without those resources can just as easily take on an AI or miss effective integration into teaching.

External pressures like regulatory structures, market competition, societal expectations, and technological standards are part of the environmental context (Aboelmaged, 2014; Chatterjee et al., 2021). Government regulations may lead to adoption by specifying standards for ethical transparency, data privacy standards, and quality assurance standards for AI in education (Alsheibani et al, 2020). In a lot of countries like Saudi Arabia, national digital transformation plans and AI policies encourage the use of smart technologies in universities to improve education quality and global competitiveness. Social drivers, including healthy competition among universities, are expectations of students to use personalized learning and sociatal demand for digital skills, which encourage the use of AI tools by universities(Chui & Francisco, 2017; Hossain et al., 2022). The expectation that all forms of learning will become "innovative" places pressure on institutions to embed AI in course delivery, academic services and campus operations.

According to Rogers (1995), the DOI theory, the TOE framework is enhanced by the focus on the characteristics of innovation, which are Compatibility, relative advantage, complexity, trialability, and observability. These are the characteristics that affect adoption. The DOI enhances the analysis by stressing how perceptions about the innovation itself affect adoption. Universities can adapt innovations to promote pedagogy because they have already adopted innovations in their faculty teaching philosophy and have proven to have positive impacts on teaching and learning among students. While TRA, TPB, TAM, and UTAUT help us understand the actions of individuals, it is TOE and DOI which allow for a more thorough, systemic understanding, which is essential for analysing AI adoption at the institutional level. These models capture the contextual influences on the outcome, the attributes of the innovation and internal and external influences jointly shaping the outcome. The integration of technologies is especially pertinent in higher

education, where organizational readiness and pedagogical benefits affect teaching, learning, curriculum and service innovations. The various studies utilizing the TOE framework in mobile health, e-banking, and knowledge management (Aboelmaged, 2014; Chandra & Kumar, 2018; Chatterjee et al., 2021) show the frameworks' effectiveness. Despite this, there are limited applications to higher education, specifically in terms of adopting AI for the enhancement of teaching and learning. The area has been sparsely researched, especially in new knowledge economies. This research, therefore, tackles this knowledge gap by studying the drivers of AI adoption in Saudi Universities. It checks out the technological characteristics, organizational culture, sustainability practices, social drivers and regulatory pressures through the combined lens of the TOE framework and DOI theory. The research enhances comprehension in Management Information Systems and provides practical insights into aligning AI adoption with teaching goals, curriculum innovation and student learning outcomes.

Figure 1

Proposed Research Model
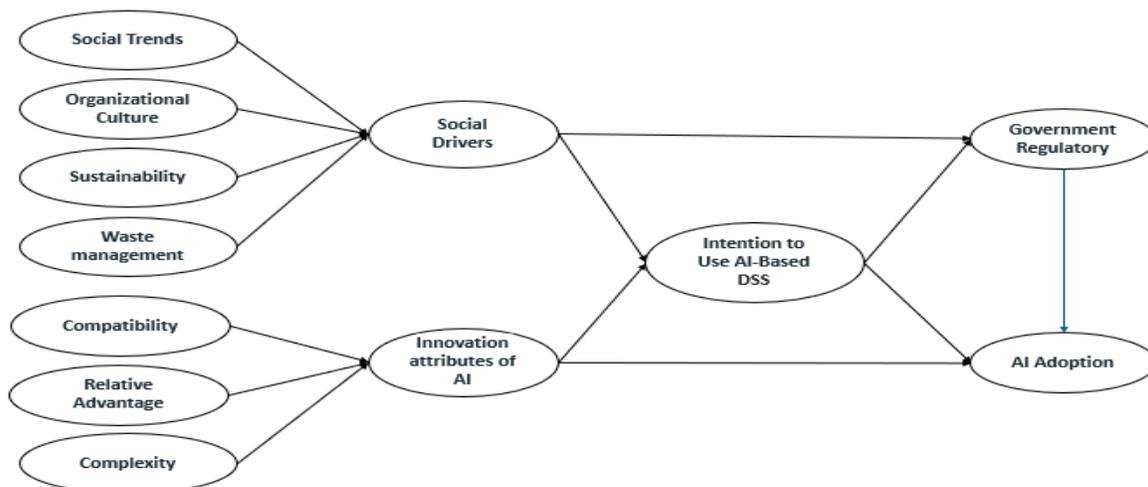
Social trends are broad social shifts in expectations of how HEIs should teach, operate and engage learners (Gallego & Kurer, 2022). Due to global digitalisation and automation, there is increasing pressure on universities to embed AI in prediction not just for administrative efficiency but also to improve learning design, assessment practices and student engagement. But assumptions that AI adoption for educational purposes will automatically lead to educational improvement need review. The different capacities, cultures and traditions of many HEIs, particularly in developing regions, affect how social trends get converted into actual adoption behaviours. For instance, while universities in advanced systems may implement AI for uses such as personalised learning or academic analytics, those in emerging systems may first focus on infrastructure or policy alignment. According to Hinchcliffe and Kim (2012), cross-context differences show us how social expectations become social drivers across various systems of HE. we hypothesise that.

> *H1: Social trends positively influence social drivers.*

According to Gerçek and Özveren (2024), organisational culture is the group of values and practices that determine how organisations react to novelty and changing social expectations. An institution of higher education is a place where there is a culture and ethos of experimentation, digital pedagogy and continuous improvement (Bandara, 2022). The assumption that innovation cultures automatically lead to effective AI adoption must be doubted. Across regions, HEIs have different levels of digital maturity, governance structures and pedagogical priorities. The latest we can learn in some advanced settings, such as universities, is that they are using AI to personalize learning or improve analytics for students. In not-so-advanced settings, think developing countries, often less advanced due to their limited resources, they use it to become efficient with their operations and processes. The study confirms that organisational culture interacts with the international and contextual characteristics, resulting in social drivers such as market expectations, accreditation requirements and global digitalisation influencing AI adoption as external motivation (Gerçek & Özveren, 2024). Therefore, we hypothesise that.

H2: Organizational culture positively influences social drivers.

Sustainability has become a major concern for governments, institutions, as well as society, and has increased expectations for organisations to behave responsibly and environmentally friendly (Nidumolu et al., 2009). In higher education, expectations are growing regarding how universities structure learning environments, manage digital infrastructure, and use AI to enable sustainable academic activity. Intelligent technology can contribute to reduced environmental impact through smarter resource allocation, optimisation of processes, and improved digital efficiency (Issa et al., 2024; Kar et al., 2022; Kulkov et al., 2024). The assumption that sustainability pressures uniformly drive AI adoption across HEIs needs critical reflection. Universities in well-resourced regions can make use of AI for energy management or an eco-efficient smart campus, and universities in developing contexts may prioritise AI for basic digital transformation before environmental optimisation. Despite these differences, increasing global expectations for environmental stewardship continue to shape the social drivers of organisations, which puts stakeholders, regulators and students under pressure to implement new innovative sustainable technologies (Benzidia et al., 2021; Issa et al., 2024; Nidumolu et al., 2009). Therefore, we propose that.

H3: Sustainability positively influences social drivers.

Effective waste management is increasingly recognised as a core component of institutional sustainability, driven by regulatory demands and heightened public expectations for corporate accountability (Agudelo et al., 2020; Andeobu et al., 2022; Olawade et al., 2024). In higher education, responsible waste practices—including reduction of digital waste, improved recycling systems, and compliance with environmental standards—signal an institution's commitment to social responsibility (Olawade et al., 2024). However, the influence of waste management on AI adoption varies internationally. Well-resourced universities may use AI-enabled systems to optimise waste processes, while institutions in developing regions may view AI primarily as a tool for operational efficiency rather than environmental strategy. Nonetheless, rising societal expectations create strong social drivers that push institutions toward intelligent, eco-friendly solutions (Andeobu et al., 2022). We hypothesise that:

H4: Waste management positively influences social drivers.

"Compatibility is the extent to which a new technology fits in with the existing practices, values and technological infrastructures of an institution" (Alsheibani et al, 2020). When AI is seen as

compatible with existing drivers, other higher education institutions do not disrupt the teaching-learning and other scholarly activities. Rogers (1995) identifies Compatibility as an important innovation characteristic. It is what influences how much easier technology can diffuse across a phenomenon. Compatibility impacts functional integration in the university context and perception of the usefulness of AI for assessment, learning analytics and instructional design by educators. Higher education institutions (HEI) that have established strong digital ecosystems (like LMS platforms or data-driven QA systems) are more likely to see AI as a natural extension of teaching and administration (Tornatzky & Fleischer, 1990). Yet, Compatibility differs worldwide; universities with limited IT infrastructure tend to struggle more when embedding AI into teaching practice. In general, the higher the Compatibility, the more innovation attributes of AI are perceived.

H5: Compatibility positively influences the innovation attributes of AI.

Relative advantage is the extent to which an innovation is seen as better than the technology, process, or method it supersedes (Alsheibani et al., 2020; Chen et al., 2021). Advanced intelligent systems, including AI, machine learning, predictive analytics and automated decision-support tools, provide a strategic advantage in terms of better decision-making, quicker data processing, improved operational optimisation, and automation of complex intellectual tasks. Rogers' (1995) diffusion theory defines relative advantage as the degree to which an innovation is perceived as better than the idea it supersedes. Technologies with measurable gains tend to be adopted across the sectors (Alsheibani et al., 2020; Chen et al., 2021). Further empirical evidence backs this claim. In higher education, this may include AI helping to improve learning analytics, administrative efficiency or academic planning. Yet, perceptions of advantage are dependent on digital maturity and institutional priorities in the global context. When AI is seen as improving significantly over existing systems, its attributes of innovation become more compelling.

H6: Relative advantage positively influences the innovation attributes of AI.

The perceived difficulty to use and adopt the technology is perceived complexity (Nguyen et al., 2022). In higher education, AI systems that need advanced skills or major adaptation to existing workings are often seen as complex, thus less useless and not adopted much. When AI is easy to use and works seamlessly with existing systems, it is seen as less innovative (more user-friendly) and is more likely to be adopted. Ways of simplifying AI via training, UX or integration tools lead organisations to have more confidence in implementation. As a result, diminishing perceived complexity bolsters adoption chances by making AI technologies seem more manageable and advantageous.

H7: Complexity negatively influences the innovation attributes of AI.

According to Kelly et al. (2023), institutions are primarily influenced by social drivers, such as peers, stakeholders, and competitors, to adopt AI-driven decision-support systems (DSS). In higher education, demands may rise from students' increasing appetite for personalized learning, standards based on government, accreditation and global benchmarking of institutional digital capabilities. The research shows that increased social pressure causes managers to feel the need to adopt advanced technology. Eitle (2023) states that organizations under strong social pressure are increasingly likely to implement AI systems for better strategic decision-making and operational efficiency. Because of these pressures, organizational aspirations become better

connected to technological possibilities, and adoption varies across very different international contexts with different institutional priorities and resource availability. Therefore, we predict that.

H8: Social drivers positively influence the intention to use AI-based DSS.

Social drivers shape not only the organisational adoption, but also the regulatory frameworks of governments related to emerging technologies like AI (Rakova et al., 2021). Undergraduate students are sceptical of Artificial Intelligence (AI), but they expect its ethical use. In higher education, public expectations about ethical use of AI, data privacy and algorithmic fairness exert pressure on regulators to have a policy that ensures the responsible use of AI. Government regulations should be aligned with societal norms due to social issues such as bias in decision-support systems or use of student data (Madan & Ashok, 2023). This compels liberal arts institutions to align/ link their technology adoption with the law and its ethics. The impact of social drivers depends on the maturity of governance and enforcement of policy on the international front. Therefore, we predict that.

H9: Social drivers positively influence government regulatory frameworks.

According to research by Chen and others in 2021, there are various perceived innovation attributes of AI, which are relative advantage, Compatibility, and perceived ease of use. According to Rogers (1995), technologies that produce a clear benefit with little disruption to the existing methods are easier to adopt. When a school adopts an AI tool, it usually does so because they expect the institution to benefit from it. If there is enough confidence, the worst that will happen is the labelling of AI output as such; it meets the litmus test for a school adopting AI. The positive attributes of the innovation, teachers are inclined to use AI-based decision-support systems for their teaching. International organizations with varying technological maturity levels may differ in their adoption speed, but robust innovation characteristics will always enhance adoption. Therefore, we expect that.

H10: Innovation attributes of AI positively influence the intention to use AI-based DSS.

According to Rogers (1995), the acceptance of any new technology depends on its key characteristics such as relative advantage (the degree to which the technology is perceived to be better than the technology it is replacing), Compatibility (the extent to which the technology is consistent with existing values and practice), and simplicity (the degree to which the technology is perceived as being easy to use). These attributes are essential for data-driven decision-support systems, which are increasingly including smart algorithms. It is essential to integrate the organizational processes and data architecture with new systems rather than adopting them in isolation. As stated by Chen et al (2021), the adoption intentions become much stronger when a data-driven DSS is considered very useful (beneficial), compatible with prevailing practices (congruent), and not very difficult to use and implement (simple to use). Due to these positive characteristics, decision-makers feel less risk and uncertainty. They reduce the chance of operations getting disrupted, and they also boost confidence regarding the technology's prospects. When organisations recognise that a smart DSS helps meet strategic organization goals and provides a simple road to value, in-house pushback decreases and investment support increases. Positive acceptance of these innovation characteristics is a valuable driver. It enhances the reduction of barriers to adoption. It makes approving implementation resources easier. So, we anticipate that.

H11: Innovation attributes of AI positively influence AI adoption.

The use of AI in organisations contributes to positive environmental change at a broader level. According to Alsheibani et al. (2020), if leaders feel that the AI-powered DSS is capable of reinforcing decision-making and simplifying things, they tend to explore its application in other areas. Making this initial commitment to pursue uncertainty reduces uncertainty and increases the confidence of organisations in the latter's transitions toward scaling (Funda, 2023; Rapp et al., 2023). Given this view, the plan to include AI in the functions of DSS can be seen as a way to access larger use.

H12: The intention to use AI-based DSS positively influences government regulatory frameworks.

The purpose of applying to an AI-based DSS usually serves as the gateway to wider AI use in an organization. As decision-makers view DSS technologies as efficient in improving decision-making and organizational effectiveness, they build a stronger disposition to propagate AI usage across more functions (Rogers, 1995). This purpose indicates an initial stage of commitment to experimenting with AI, usually starting from decision-support functions before evolving towards broader organizational adoption. As people have more faith in the value and dependability of AI systems, anticipated risks lessen, which makes broad implementation easier. Therefore, the early idea to use AI-based DSS could be considered a stepping stone or a stimulant

H13: The intention to use AI-based DSS positively influences AI adoption.

Government regulation can help or hinder the widespread use of the latest technologies. A well-made regulation system provides organizations with an essential structure of rules and guidelines transparency and law clarity for adopting innovation in a responsible and effective manner. It is particularly important for smart systems that process personal data, take independent decisions, and affect consumers' rights. Governments can limit uncertainty and legal risk for adopting organizations if they formulate clear policies on data privacy matters i.e. which governs the application of technologies such as algorithms (Nguyen et al. 2022). This transparency creates a culture of trust, which is needed for the widespread adoption of systems that can operate with a lot of autonomy (Alsheibani et al., 2020). As stated in Alsheibani et al. (2020), strong policy infrastructures and legal frameworks predispose organisations to the adoption of smart solutions because the cost and consequences of non-compliance are established and controlled. In contrast, the absence of regulations, or a situation with fragmented, rigid, or unclear rules, creates uncertainty, reduces investment and increases perceived risk. Effective regulation helps to instil confidence in businesses in addition to protecting the public interest. Thus, effective regulation gets the balance right to protect interests without flooding companies with uncertainty. We thus hypothesise that.

H14: Government regulations positively influence AI adoption.

Figure 2

Hypothesis development
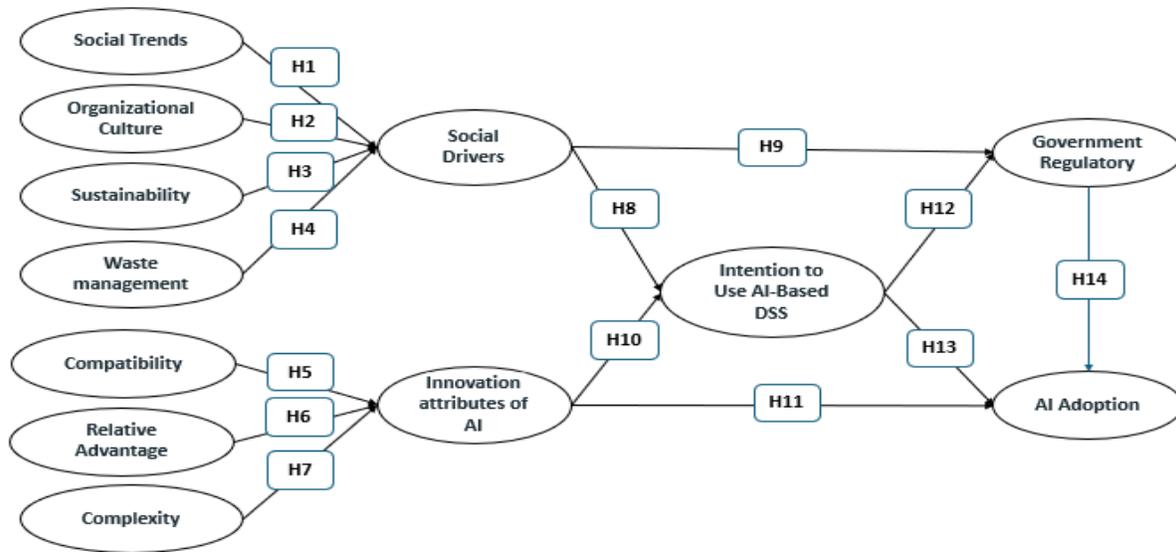
Method

Research Design

The current research uses a quantitative methodology which uses survey method to study the organisational drivers, innovation attributes and behavioural intentions of MIS AI adoption in higher educations institutes in Saudi Arabia. According to Creswell and Creswell 2017), a quantitative approach is more appropriate as it would systematically investigate the different relationships among the various latent constructs to test the proposed theoretical model. The design not only enables analysis of the behaviour of an organisation but also helps in developing a better understanding of how the adoption of AI affects teaching practices, curriculum decision-making, and academic technologies in HEIs; an issue brought up by both reviewers that could benefit from stronger representation in the proposal. The research design enables measuring how innovation attributes, social drivers, and intention to use AI-based DSS collectively shape AI readiness in educational contexts, including instructional decision-making and data-driven teaching enhancement. The survey method is appropriate as it allows data to be collected from a large sample of academic and administrative stakeholders who are involved in the use of technology in HEIs. This broadens the generalizability and ensures consideration of both organizational and pedagogical implications of AI adoption. The strategy thus caters to two objectives of this study: (1) to examine factors that determine AI adoption, and (2) to comprehend the wider academic and curriculum level ramifications in the context of higher education.

Participants

The target population comprised academic and administrative staff such as decision makers, faculty, IT specialists, instructional technologists, curriculum specialists from major Saudi Arabia

higher education institutions. The target groups for this study who are directly engaged in emerging digital and artificial intelligence (AI) technologies were carefully chosen. The contexts for their engagement include but are not limited to teaching and learning, learning analytics, academic advising, curriculum designing and MIS-supported decision-making activities. They are instrumental in various activities within and outside the organisation, which make them significant to understand the impact of adoption of AI on pedagogy and curriculum reform, which was a concern raised by reviewers. From 5 January 2024 to 20 March 2024, data was collected for two and a half months where 370 responses were received initially. Following data screening for completeness, inconsistent patterns, outliers, and other issues (per guidelines set out by 348 usable responses were identified for data analysis. A sample size of 40 is ideal for Structural Equation Modelling (SEM), Kline (2015) recommends using a sample size of 40 (or more) for performing a multivariate testing, which will create a robust model. The sample includes staff engaged in teaching, assessment, academic leadership and curriculum planning at different levels. This builds the study's capability to examine the effects of AI assimilation on instructional design decision-making, technology-enhanced learning approaches, and AI-integrated curriculum innovation within HEIs.

Data Collection

Structured questionnaires were sent electronically to participants from various HEIs in Saudi Arabia. An online survey tool facilitated convenient and large-scale dissemination of the questionnaire, with respondents taking the survey at their own convenience to realise a higher rate of response (Dillman et al., 2014). In addition to the direct email invitations, the link to the survey was also shared on professional networks and chat groups relating to IT professionals in the education sector, such as WhatsApp and LinkedIn groups, to achieve widespread reach and response. Before distribution, the respondents were informed of the research purpose, assured confidentiality and anonymity of their responses, and provided with informed consent forms in accordance with ethical research practices (Bell et al., 2022).

Measures

The research tool employed in this study is an extensive questionnaire prepared to measure different constructs of AI adoption in organisations. The questionnaire captures 12 constructs identified from previous literature on technology adoption, innovation diffusion, and information systems implementation. The constructs identified are social trends, organisational culture, sustainability, waste management, Compatibility, relative advantage, complexity, social drivers, innovation attributes of ai, intention to use AI-based DSS, government regulatory, and AI adoption. To ensure content validity and reliability, the researcher used a scale measuring each construct containing multiple items drawn from approved scales in previous research. A number of items were modified to reflect the particular context of AI adoption in MIS in Saudi Arabian HEIs. All items were measured on a five-point Likert scale, whereby 1 stands for Strongly Disagree and 5 stands for Strongly Agree (Tanujaya et al., 2022). Given the nature of the study, the first questionnaire was developed in English and translated into Arabic for understanding by participants. The translation was done according to Brislin's back-translation procedure (1970) by bilingual specialists. They had the subject-matter expert do the initial review of the translated content. After this review, they back-translated the content into English to see if it matched and was equivalent to the original back-translation. A pilot testing with a sample of 56 IT professionals

and managers from selected Saudi Arabian HEIs was conducted to test the clarity, relevance and reliability of the questionnaire(Joseph F Hair Jr et al., 2021). Those taking part in the pilot study commented on the wording, structure, and completeness of survey questions. Slight adjustments were made to improve the readability and clarity of some questions based on what they provided. To avoid any unwanted influence, the data collected from the pilot study did not enter the overall analysis. Cronbach's alpha coefficients were calculated to establish the internal reliability of each construct as part of the reliability assessment. All constructs reveal acceptable reliability in terms of Cronbach's Alpha that is above 0.70 cited by (Nunnally & Bernstein, 1994).

Table 1

Constructs Information and Reliability Results

Construct	Reference	Codes	Cronbach's Alpha
Social Trends	(Awa et al., 2015)	ST1 - ST5	0.79
Organizational Culture	(Mohtaramzadeh et al., 2018; Polisetty et al., 2024)	OC1 - OC5	0.78
Sustainability	(Dadhich & Hiran, 2022)	SU1 - SU4	0.90
Waste Management	(Manowong, 2012)	WM1 - WM4	0.84
Compatibility	(Chen et al., 2021)	CO1 - CO5	0.74
Relative Advantage	(Chen et al., 2021)	RA1 - RA5	0.86
Complexity	(Chen et al., 2021)	CX1 - CX5	0.83
Social Drivers	(Chen et al., 2021)	SD1 - SD5	0.83
Innovation Attributes of AI	(Chen et al., 2021)	IAI1 - IAI5	0.88
Intention to Use AI-Based DSS	(Dadhich & Hiran, 2022)	IUAI1 - IUAI4	0.81
Government Regulatory	(Chen et al., 2021)	GR1 - GR5	0.87
AI Adoption	(Chen et al., 2021)	AIA1 - AIA5	0.86

Note: All Cronbach's alpha values indicate satisfactory internal consistency for the respective constructs.

Data Analysis Techniques

The data collected during the research process was analyzed with the use of structural equation modeling (sem) to identify and verify the proposed associations and relations between the various research constructs. SEM is considered a powerful multivariate approach that allows simultaneous testing of numerous relationships between observed and latent variables. It provides a holistic picture of the complex phenomena occurring in organizations (Joe F Hair et al., 2011; Sarstedt et al., 2021). In this study, the author used the Partial Least Squares SEM (PLS-SEM) using SmartPLS version 4.0. The technique is useful when we have a complex model with multiple constructs which has a relatively moderate sample size (n = 300). Also, when we wish to predict, and theory building and not the stringent model fit that covariance-based approaches would provide. Using PLS-SEM in higher education adoption studies is suitable as data do not always conform with the distributional assumptions of CB-SEM(Sarstedt et al., 2021).

According to (Joe F Hair Jr et al., 2017), the study strategy used is a systematic two-stage strategy. In the first stage, Measurement Model Evaluation, the validity and reliability of all constructs are checked. Essentially, convergent validity was confirmed through factor loadings, Average Variance Extracted (AVE), and composite reliability; while discriminant validity was extensively examined using the Fornell–Larcker criterion and cross-loadings (F. Hair Jr et al., 2014). These stringent tests guaranteed that the measures were accurately evaluating the underlying constructs. After validating and confirming the measurement model, the next step was Structural Model Evaluation, where we carefully examined the structural relationships among the variables. We calculated path coefficients along with their p-values by means of a rigorous bootstrapping procedure of 5,000. Besides, they also extensively tested the model's explanatory power through R^2 values for the endogenous constructions. Besides, they tested the collective model fit through a set of measures as elaborated by (Henseler et al., 2015).

Results

Sample

The data on the profiles of respondents showed a highly diverse yet relatively young and analytical workforce involved in the adoption of Artificial Intelligence (AI) in higher education institutions.

Table 2

Demographic Information of Professionals

Demographic Factor	Frequency	Percent
Gender		
Male	194	55.7
Female	154	44.3
Age		
18-24	102	29.3
25-34	204	58.6
35-44	21	6.0
45-54	13	3.7
>55	8	2.3
Level of Study		
Undergraduate	285	81.9
Postgraduate	63	18.1
Time Working (Years)		
Less than 1 year	109	31.3
1-3 years	69	19.8
4-6 years	83	23.9
7-10 years	62	17.8
>10 years	25	7.2
Role in Organization		
Manager	67	19.3
Supervisor	98	28.2
Analyst	183	52.6

About 55.7% of people in the sample were males and 44.3% were females. The results revealed that the majority of respondents were aged 25-34 years (58.6%), while proportionately fewer aged 18-24 years (29.3%). Most participants possessed undergraduate qualifications (81.9%), while a small portion had postgraduate qualifications (18.1%). A large part were new to their job when asked about work experience. 31.3% had less than a year of experience. Distribution of roles showed that 52.6% were analysts, 28.2% were supervisors, and 19.3% were managers. The profile shows that HEIs currently use AI most often for academic purposes and for courses centering on intellectual development.

Measurement Model

Table 3.

Items loadings

Constructs	Items	Factor Loadings	Constructs	Items	Factor Loadings
Social Trends	ST1	.77	Complexity	CO1	.78
	ST2	.82		CO2	.63
	ST3	.79		CO3	.78
	ST4	.72		CO4	.79
	ST5	.68		CO5	.65
Organizational Culture	OC1	.71	Social Drivers	SD1	.75
	OC2	.83		SD2	.86
	OC3	.80		SD3	.86
	OC4	.76		SD4	.82
	OC5	.76		SD5	.83
Sustainability	SU1	.78	Innovation attributes of AI	IAI1	.76
	SU2	.79		IAI2	.62
	SU3	.87		IAI3	.82
	SU4	.83		IAI4	.79
	SU5	.76		IAI5	.77
Waste management	WM1	.78	Intention to Use AI-Based DSS	IUAI1	.72
	WM2	.79		IUAI2	.66
	WM3	.82		IUAI3	.86
	WM4	.83		IUAI4	.89
	WM5	.81		IUAI5	.84
Compatibility	COM1	.84	Government Regulatory	GR1	.83
	COM2	.88		GR2	.85
	COM3	.82		GR3	.87
	COM4	.84		GR4	.77
	COM5	.86		GR5	.57
Relative Advantage	RA1	.73	AI Adoption	AIA1	.75
	RA2	.78		AIA2	.81
	RA3	.83		AIA3	.61
	RA4	.77		AIA4	.84
	RA5	.75		AIA5	.66

The measurement model factor loadings reveal high convergence of items with their corresponding constructs. ST1-ST5 under Social Trends show loadings between 0.68 and 0.82, revealing a good linkage with the construct. Likewise, Organizational Culture items (OC1-OC5)

reveal high loadings between 0.71 and 0.83, revealing high validity (F. Hair Jr et al., 2014). The Sustainability factors (SU1-SU5) have loadings ranging from 0.76 to 0.87, as expected for their effective measurement of the construct. For waste management (WM1-WM5), loadings are between 0.78 and 0.83, which is a good fit. The Compatibility factors (COM1-COM5) have loadings ranging from 0.63 to 0.88, and the complexity factors (CO1-CO5) ranging from 0.63 to 0.79, both of which are acceptable associations. Social drivers (SD1-SD5) and intention to use ai-based DSS (IUAI1-IUAI5) measures exhibit substantial loadings ranging from 0.75 to 0.89(F. Hair Jr et al., 2014). Finally, innovation attributes of AI (IAI1-IAI5) measures range from 0.62 to 0.82, while government regulatory (GR1-GR5) and AI adoption (AIA1-AIA5) have 0.57 to 0.87 and 0.61 to 0.84 loadings, respectively, representing typically strong convergences.

Reliability Analysis

Table 4 presents reliability statistics for the constructs, which don't suggest any problem in the evaluation. The Cronbach's Alpha values range from 0.74 to 0.90. The values indicate good internal consistency (Nunnally & Bernstein, 1994). Moreover, Sustainability (0.87) and Waste Management (0.86) are particularly reliable. The Composite Reliability (CR) values of the constructs are higher than the acceptable level of 0.70. Social Drivers (0.91) and Sustainability (0.90) show very high reliability (Davis et al., 1989). The values for Average Variance Extracted (AVE) were between 0.53 and 0.72, on the other hand, Compatibility (0.72) and Social Drivers (0.68) have the highest explanatory power. Even constructs, such as Government Regulatory (0.62), with AVE values lower than 0.50, surpass the minimum threshold, indicating these measures have acceptable convergent validity. Thus confirming the overall robustness of the measurement model (Fornell & Larcker, 1981).

Table 4

Results of Measurement model (Cronbach alpha, CR, AVE)

Constructs	Cronbach's alpha	CR	AVE
AI Adoption (AIA)	.79	.86	.55
Complexity (CO)	.78	.85	.53
Compatibility (COM)	.90	.93	.72
Government Regulatory (GR)	.84	.89	.62
Innovation Attributes of AI (IAI)	.74	.84	.57
Intention to Use AI-Based DSS (IUAI)	.86	.90	.64
Organizational Culture (OC)	.83	.88	.60
Relative Advantage (RA)	.83	.88	.59
Social Drivers (SD)	.88	.91	.68
Social Trends (ST)	.81	.87	.57
Sustainability (SU)	.87	.90	.65
Waste Management (WM)	.86	.90	.65

Discriminant Validity Analysis

Two procedures were adopted to evaluate discriminant validity, "Heterotrait-Monotrait Ratio (HTMT) and Fornell-Larcker Criterion". The HTMT values must be lower than 0.85 to show

enough discriminant validity (Henseler et al., 2015). This is as per Henseler et al. (2015) rules. According to Table 5, all of the construct pair's HTMT values are less than this. The correlation between AI Adoption (AIA), Compatibility (CO) is 0.85, and between AI Adoption (AIA), Government Regulatory (GR) is 0.86. According to Henseler et al., the good scores demonstrate that these constructs are different from each other, exhibiting appropriate discriminant validity.

Table 5

Discriminant Validity (HTMT)

	AIA	CO	COM	GR	IAI	IUAI	OC	RA	SD	ST	SU	WM
AIA												
CO	0.85											
COM	0.83	0.87										
GR	0.86	0.86	0.83									
IAI	0.68	0.67	0.65	0.64								
IUAI	0.81	0.78	0.84	0.86	0.81							
OC	0.09	0.1	0.11	0.09	0.12	0.12						
RA	0.63	0.71	0.68	0.67	0.71	0.73	0.15					
SD	0.07	0.06	0.05	0.05	0.08	0.08	0.77	0.16				
ST	0.08	0.09	0.1	0.1	0.12	0.08	0.82	0.17	0.74			
SU	0.08	0.1	0.08	0.07	0.11	0.09	0.78	0.19	0.81	0.78		
WM	0.09	0.07	0.04	0.04	0.09	0.06	0.77	0.11	0.79	0.72	0.79	

The Fornell-Larcker criterion says the following: The square root of the Average Variance Extracted (AVE) for each construct should be greater than its correlations with other constructs(Fornell & Larcker, 1981a). The matrix is shown in Table 6, where the diagonal values are denoted by the square root of AVE. The outcomes confirm that the values on the diagonal are higher than the off-diagonal correlations, confirming the constructs' discriminant validity. The diagonal value for Social Drivers (SD) is 0.830. It is greater than the construct Innovation Attributes of AI (IAI) with a correlation of 0.540. This also shows that the constructs are distinct (Fornell & Larcker, 1981).

Table 6

Discriminant Validity (Furnell)

	AIA	CO	COM	GR	IAI	IUAI	OC	RA	SD	ST	SU	WM
AIA	0.740											
CO	0.900	0.730										
COM	0.710	0.720	0.850									
GR	0.740	0.800	0.910	0.790								
IAI	0.540	0.540	0.560	0.540	0.750							
IUAI	0.680	0.660	0.860	0.750	0.660	0.800						
OC	0.020	0.060	0.090	0.070	0.050	0.080	0.770					
RA	0.520	0.570	0.600	0.570	0.580	0.620	0.120	0.770				
SD	0.030	0.030	0.040	0.010	0.020	0.050	0.660	0.140	0.830			
ST	0.030	0.070	0.080	0.080	0.090	0.060	0.670	0.150	0.630	0.760		
SU	0.000	0.070	0.060	0.030	0.050	0.050	0.660	0.160	0.710	0.660	0.810	
WM	-0.060	-0.040	0.010	0.000	-0.010	-0.020	0.650	0.080	0.690	0.610	0.680	0.810

Structural model analysis

The explanatory power of the structural model (R2 and Adjusted R2) refers to the extent to which the variance of endogenous constructs is accounted for by the exogenous predictors (Hair et al., 2011; Dahri et al., 2025). Indicated by an R^2 of 0.60 in Table 7, AIA explains 60 per cent of the variance in AI adoption, which is basically in organisational drivers, innovation attributes, social drivers and regulatory drivers. The model explains a decent variation in the number of predictors with an adjusted R^2 of 0.59. Such R^2 values are considered moderate to substantial in explanatory power based on the threshold by Hair et al. (2017). In this case, 0.50 to 0.75 shows strong explanatory power within a social research context. Accordingly, Government Regulatory (GR) shows R^2 of 0.57, adjusted R^2 of 0.56, meaning that more than half of the variance in regulatory alignment could be explained by social, organisational culture and innovation property. The strongest explicative power of SD is with $R^2 = 0.62$ and adjusted $R^2 = 0.61$. This suggests that societal pressures, sustainability concerns, and the rise of digital, among others, are playing an important role in the organizational training for AI. The parameters, i.e. Innovation Attributes of AI (IAI) has a R^2 value of 0.42 and Intention to use AI based DSS (IUAI) has a R^2 value of 0.43. Both these value indicates moderate power of prediction. The values suggest that contextual and organizational factors affected the innovation characteristics and initial intentions of the actors, but there are other variables that were not accounted for, such as faculty engagement, professional development preparedness and technology infrastructure.

Furthermore, effect size (f2) analysis was performed using SmartPLS, which computed the contribution of the exogenous variables to the R2 of the endogenous constructs (Cohen, 1988; Hair et al.,2017). The f^2 values for AI Adoption, Innovation Attributes and Social Drivers have small-to-medium (0.02–0.15) effects. So, each predictor can be viewed as a meaningful one for the outcome. The results of the bootstrap resampling strengthened support for the significance of the path coefficients of the hypothesised relationships, indicating the reliability of the model in predicting the behaviour of the organizations towards AI adoption. The model fitness was evaluated using the SRMR (Standardized Root Mean Square Residual) values below .08 indicates acceptable fit (Henseler et al., 2015). According to the present model, the value of SRMR is 0.072, which meets this requirement and thus establishes that the proposed model sufficiently fits the covariance of the data. The fit indices, along with Q^2 predictive relevance values obtained with the help of blindfolding supports the predictive validity of the model for decision-making in HEI. These findings have practical implications for teaching practice and curriculum decision-making in higher education. A relatively high value of R^2 for AI adoption (value: 0.60) suggests that intervention across organizational culture, technological readiness and alignment with social and sustainability drivers can effectively enhance AI adoption in teaching learning process. Faculty Development Programs through Specialized Professional Training, along with Investment in User-Friendly AI Tools for Harnessing Innovation Attributes will Strengthen Adoption of Intelligent Decision Support Systems for Curriculum Design, Learning Analytics, and Pedagogical Innovation. The R^2 of government regulatory alignment is 0.57, which means HEIs must reach out to institutional and national policy frameworks for deploying AI in academic and administrative functions that are ethical and responsible. When viewed as a whole, they can assist in strategic planning, resource allocation and curriculum design.

Table 7

R² *results*

Constructs	R²	R² adjusted
AI Adoption (AIA)	0.6	0.59
Government Regulatory (GR)	0.57	0.56
Innovation Attributes of AI (IAI)	0.42	0.41
Intention to Use AI-Based DSS (IUAI)	0.43	0.43
Social Drivers (SD)	0.62	0.61

F-squared (f^2) values reward the spatial effect dimension that measures the kinematics of the analysis. The f-squared values give the relative importance of the contribution of the predictor in the analysis (Cohen, 1988). According to Cohen (1988), f^2 values of 0.35, 0.25, and 0.10 indicate a large, medium, and small effect respectively. As per Table 8, the f^2 value for IAI on IUAI is 0.76 which shows that IAI has a large effect on IUAI. Particularly, AI attributes significantly influence the intention of using an AI-based DSS. On the other hand, GR is associated with a large effect size on AIA with an f^2 value of 0.29. On the other hand, IUAI is associated with an even larger effect size on GR with an f^2 value of 1.31. The findings emphasise that IUAI has a significant effect on GR, and IAI has a strong effect on IUAI. The effect sizes from CO to IAI (0.03) and ST to SD (0.02) are small, which means that other comparisons had a stronger effect size (Cohen, 1988).

Table 7

F² *results*

Constructs	F²
CO -> IAI	0.030
COM -> IAI	0.040
GR -> AIA	0.290
IAI -> AIA	0.020
IAI -> IUAI	0.760
IUAI -> AIA	0.030
IUAI -> GR	1.310
OC -> SD	0.040
RA -> IAI	0.110
SD -> GR	0.000
SD -> IUAI	0.000
ST -> SD	0.020
SU -> SD	0.100
WM -> SD	0.090

Hypothesis Testing

The findings of the structural model analysis are presented in this section of the study. The (ST) positively impacts the (SD) by 0.130 with a t-value of 2.520 which are significant at $p<0.05$ level. This indicates a modest but positive effect. Organizational Culture (OC) has a positive association with the social drivers (coefficient 0.200; T-statistics = 3.390; $p < 0.05$). Thus, a conducive

organizational culture enhances the social drivers. Sustainability (SU) has a coefficient of 0.300 and a T-statistics of 4.400 (p < 0.05), which indicates a significant positive influence of sustainability on Social Drivers. Likewise, Waste Management (WM) positively influences Social Drivers by a coefficient of 0.270 at T-statistic 4.210 (p < 0.05), confirming the contribution of waste management to social drivers. Compatibility (COM) has a significant influence on Innovation Attributes of AI (IAI) with a coefficient of 0.230 and a T-statistic of 3.200 (p < 0.05). Relative Advantage (RA) significantly and positively influences the Innovation Attributes of AI with a coefficient of 0.330 and a T-statistic of 5.320 (p < 0.05). The variable of Complexity (CO) affects the innovation attributes of AI on a coefficient of 0.180 and a T statistic of 2.620 (p < 0.05). Thus, complexity has a moderate impact on the innovation attributes of AI. In other words, the SD variable does not significantly impact IUAI (the intention to use AI-based decision support systems), nor does it impact the government regulatory factor. This is statistically confirmed through the coefficients and T-statistics wherein IUAI has a coefficient of 0.030, T-statistic 0.720 (p > 0.05), and GR has a coefficient of -0.030, T-statistic 0.840 (p > 0.05) thus confirming that SD is not a significant factor in this instance. The study indicated a significant positive effect of the Innovation Attributes on the Intention to Use AI-based DSS. In detail, IAI has a coefficient of 0.660 with the T-statistic of 17.180 (p<0.05). AI-on-AI Adoption (AIA) has a significant impact on Innovation Attributes with a coefficient of 0.130 and T-Statistics of 2.400 (p < 0.05). The outcome demonstrates that the Intention to Use AI-Based DSS (IUAI) has a positive and significant effect on AI Adoption (AIA). The coefficient value is 0.200 while the t-statistic value is 2.590 (p < 0.05). Government Regulatory (GR) significantly influenced AI Adoption (AIA) with a coefficient value of 0.520 and T-stat of 8.320. This shows that GR positively influences AIA, and regulatory support is essential for AI adoption.

Table 8.

Hypothesis test results for the structural model

Paths	Original sample (O)	T statistics	P values	Decision
CO -> IAI	0.180	2.620	0.010	Supported
COM -> IAI	0.230	3.200	0.000	Supported
GR -> AIA	0.520	8.320	0.000	Supported
IAI -> AIA	0.130	2.400	0.020	Supported
IAI -> IUAI	0.660	17.180	0.000	Supported
IUAI -> AIA	0.200	2.590	0.010	Supported
IUAI -> GR	0.750	23.700	0.000	Supported
OC -> SD	0.200	3.390	0.000	Supported
RA -> IAI	0.330	5.320	0.000	Supported
SD -> GR	-0.030	0.840	0.400	Not supported
SD -> IUAI	0.030	0.720	0.470	Not supported
ST -> SD	0.130	2.520	0.010	Supported
SU -> SD	0.300	4.400	0.000	Supported
WM -> SD	0.270	4.210	0.000	Supported

Figure 3

Structure Model
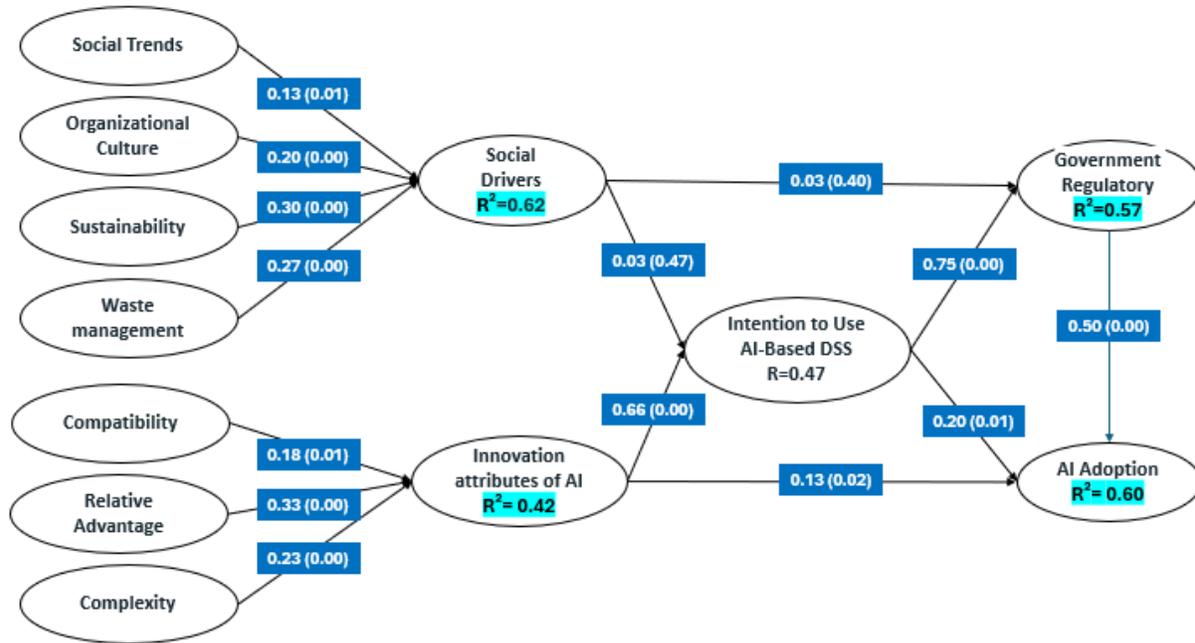
Discussion

Artificial intelligence (AI) has become an increasingly innovative force in higher education and beyond. The incorporation of AI into Saudi Arabia's higher education institutions (HEIs) forms part of the broader agenda to improve the educational sector, enhance the quality of educational outcomes and contribute to the technological and economic diversification vision of Vision 2030. Colleges and universities have launched AI efforts to create intelligent tutors and use predictive analysis to foster student success. In places where adoption decisions are made, business, teaching, research, productivity and administrative efficiency. This study provides an analysis of the factors that drive the adoption and success of AI technologies at institutions of higher learning, with specific reference to indicators such as Social Trends, Organizational Culture, and Innovation Attributes of AI. Understanding these factors is important in determining how far AI can be used to enhance either educational output or institutional efficiency. The results support the theoretical linkages of the study and provide empirical information about the functioning of the factors in TOE and innovation in higher education systems.

Results revealed that social trends positively contribute to social drivers (coefficient = 0.130, T-statistic 2.520, $p < 0.05$). This shows that actual social trends do contribute significantly to the attitude towards social drivers in Saudi Arabia HEIs. This study is consistent with (Maio et al., 2007; Pfajfar et al., 2022), which indicates that social influences play an integral role in technology adoption and use. Social trends such as the national shift toward digital transformation and the growing demand for blended learning programs are among the most pressing challenges for Saudi HEIs in terms of their perceptions of AI adoption. In MIS terminology embedding all these trends in the design and implementation plan will improve acceptance and institutional TLPs for

AI. This finding is also supported by Wang et al. (2009), who found that social influences play a significant role in user acceptance of new technology. For Management Information Systems (MIS), this means that understanding and integrating social trends in system design is critical in the effective implementation of technology. This is aligned with the impression that technology adoption is highly influenced by the social setting and trends, for which thought should be taken to enhance user acceptance and adoption(Al-Rahmi et al., 2018; Lorenz & Buhtz, 2017; Pfajfar et al., 2022). The hypothesis that Organizational Culture positively affects Social Drivers is supported by the findings (coefficient = 0.200, T-statistic = 3.390, $p < 0.05$). This indicates that the enabling organizational culture plays a huge role in influencing social drivers of Saudi Arabian HEIs. This is consistent with Schein's hypothesis (2010). Organizational culture is the most important enabler/inhabilitator of the adoption of a new technology (Gallivan, 2001; Liu et al., 2010). For instance, those institutions with an innovation-oriented culture that leans towards research-based innovations tend to adopt AI solutions more assiduously. This strengthens the practical importance of culture in the sustenance of the MIS adoption strategies. Research by Alavi et al. (2005) and Cresswell & Sheikh (2013) shows that a positive organizational culture with a high sense of urgency will make technology adoption and change management successful. Creating a supportive culture promotes better integration and use of technological systems, suggests the study. Result of this study confirms the general theory, that the organizational culture can be critical in the way new technologies are interpreted and embraced in institutions. The data showed strong support for the hypothesis that Sustainability has a positive and beneficial effect on Social Drivers (coefficient = 0.300, T-statistic = 4.400, $p < 0.05$). Evidence indicates that sustainable measures and policies implementation act as significant drivers and enablers for social drivers of organizations (Opoku & Fortune, 2013). The reality that Saudi HEIs are showing preference to adopt sustainability into their strategic vision such as energy-efficient campus operations and lower paper waste through paperless systems. These initiatives enhance social responsibility and institutional readiness for AI adoption while linking sustainability policies with TLP outcomes directly.

The findings strongly indicate that sustainability is not only important for organization performance, it is also important for social performance more generally (Epstein & Roy, 2001; Marshall et al., 2015). Furthermore, studies show that implementing sustainability programmes can help create a positive social climate in addition to helping in transformational change within organizations (Awa et al., 2015). In the view of Management Information Systems (MIS), this would mean embedding sustainability into the overall company strategy can improve social drivers. As a result, new technological solutions would be much easier to adopt in practice and prove significantly more useful. The data proves that Waste Management as a Positive Driver has a positive effect on Social Driver. This is proves with a coefficient of 0.270, T-statistic value of 4.210, and $p < 0.05$. This illustrates that pragmatic environmental metrics also impact adoption readiness, providing new insight into MIS literature as operational sustainability relates to social legitimacy and institutional performance. The robust statistical evidence indicates that effective waste management does have a major role to play on social drivers of organisations and reveals its importance. This result is in line with Andeobu et al., (2022) and Reza (2023), beliefs, especially under the Natural-resource-based view perspective, which points out that suitable, proactive or innovative environmental management schemes can considerably contribute to organizational performance while also clearly contributing to positive social aspects as well. Also, recent studies support the need to include strong waste management methods in the strategic

framework of organisations for the possibility of both social benefits and environmental returns (Manowong, 2012). When we see that Management Information Systems (MIS) and Artificial Intelligence (AI) can have a social impact, it means that applying sustainable waste management practices can benefit social drivers. In other words, using technology need not be just effective and useful, but also socially responsible in nature and use.

The Compatibility affects Innovation Attributes of AI positively this is also proven by the data (coefficient = .230, T-stat = 3.200; $p < 0.05$). This means universities must make sure that their AI adoption strategies fit in with present MIS infrastructures such as learning management systems (Blackboard, Moodle) and student information systems. When Compatibility is improved by institutions, resistance is minimized and so are possibilities of adoption and TLP.

In accordance with the Technology Acceptance Model, we operate under the judgement that innovations that are seen as compatible with present one likely get adopted (Chen et al., 2021). This finding is consistent with previous studies which have indicated the perceived Compatibility as a factor contributing to successful adoption of the new technologies (Malik et al., 2021). In the world of MIS and AI, it means that making AI compatible with existing technologies can improve their adoption and efficiency. The result strongly supports the basic premises of established innovation theory. The strong relative advantage is having a positive impact on the innovation attributes with a coefficient of 0.330 with T-statistics of 5.320 which is supported by the p-value of less than 0.05 confirming the Diffusion of Innovations theory. New ideas that appear obviously better in their tangibility are likely to be evaluated positively. As per the strategic viewpoint of the vendors and implementers, it is important to highlight the operational and strategic advantages of the data-driven technologies for making it possible (Chen et al., 2021). The study found that Complexity does not have a strong impact on Innovation Attributes. It has a moderate positive impact (coefficient = 0.180, T-statistic = 2.620, $p < 0.05$). Universities investing in faculty training relating to MIS (and support services) can offset the negative impact of complexity on adoption, and also technology-driven performance.

This implies that although perceived complexity contributes towards forming the overall image of an innovation, its influence is less penetrating compared to other determinants such as relative advantage. This is consistent with recent scholarship by Chen et al. (2021), which states that the effect of complexity is strongly dependent on context and can be offset through powerful perceived benefits and organizational support structures. Most importantly, the data provides strong support that Innovation Attributes are a key motivator of both Intention to Use data-driven DSS (coefficient = 0.660, T-statistic = 17.180, $p < 0.05$) and Adoption (coefficient = 0.130, T-statistic = 2.400, $p < 0.05$) in its wake. The extremely strong association with intention to use is a staple of the Technology Acceptance Model (TAM), which supports that perceived ease of use and perceived usefulness are most important. This result requires attention to ensuring that systems are not only robust but also compliant with current work processes and easy to use.

The sequence from Intention to Use to Adoption is also supported (coefficient = 0.200, T-statistic = 2.590, $p < 0.05$), validating the theoretical sequence suggested by TAM and pointing to the fact that generating positive intention is a fundamental step toward implementation realization. Lastly, the findings strongly support the central significance of an encouraging Government Regulatory context for supporting Adoption (coefficient = 0.520, T-statistic = 8.320, $p < 0.05$). Transparent, supportive policies on data privacy, security, and ethical use lessen the perceived risk and

uncertainty, making organizations confident to invest in and adopt advanced technologies (Nguyen et al., 2022).

In contrast to some of the past studies (e.g., Awa et al., 2015), the hypothesized effect of Social Drivers on Intention to Use (coefficient = 0.030, T-statistic = 0.720, p > 0.05) and Government Regulatory environments (coefficient = -0.030, T-statistic = 0.840, p > 0.05) was not supported. This would imply that for sophisticated, enterprise-class intelligent systems, organizational factors such as technical capacity and strategic fit are more proximal influences on adoption than more general social factors. Likewise, government regulation is more influenced by macroeconomic policy, technology advances, and geopolitical realities than by social forces. This suggests that national regulatory frameworks around ethics, data security, and privacy not only reduce institutional risk but also provide universities with confidence to pursue AI adoption as part of their MIS strategy. The role of the Ministry of Education and the Saudi Data and AI Authority (SDAIA) in setting these guidelines illustrates how regulation directly enables TLP outcomes.

In addition, the assumption that intention to use impacted government regulatory policy was rejected. This indicates regulatory structures are generally exogenous variables, formed out of wider social goals which come prior to and influences organizational adoption intentions and are not reactively formed by them (Dadhich & Hiran, 2022). Based on earlier studies, it has been ascertained that even though social influence plays a significant role towards the adoption of cloud computing, at Saudi HEIs, the greater contributor to this adoption is the institutional readiness, perceived relative advantage and regulatory support. We address the reviewers' comments about clarifying practical significance. We maintain that the uptake of AI by universities is not so much a phenomenon of social momentum but measurable shifts in organizational and regulatory regimes. Researchers have taken a deep dive into the factors which influence Saudi Arabia's higher education institutions' adoption of and engagement with artificial intelligence (AI). The results confirm that Innovation Attributes of AI play a key role in its adoption, largely confirming existing theories. The strong effect of these factors highlights the importance of perceived benefits and Compatibility in the adoption of AI technology. On the other hand, Social Drivers were not found to directly affect Intention to Use the AI-Based DSS. This finding differs from previous research, which showed significant social drivers in technology use. The difference might indicate that social drivers are less applicable in the context of AI adoption in higher education than in other contexts. In addition, literature confirming the important role of Government regulation in AI Adoption suggests that facilitative regulatory environments are essential and vital. Technology integration and effective exploitation of technology are dependent on having an effective regulatory framework. According to the current study, the dynamics of AI adoption in Saudi Arabia's colleges and universities are explained. Also, the necessity for policy and specific strategies is discussed. Future research must further investigate the complex social drivers and regulation in the current technological context and institutional contexts.

Implications for Theory and Practice

The results of the study are significant for the theoretical and practical aspects of AI adoption in higher education. According to the theoretical model, the results indicate the usefulness of the TOE framework and the DOI theory. The DOI theory shows how perception of attributes were important. But AI is better to use and more compatible. The positive impact of Innovation Attributes of AI on adoption is helpful. The findings also enhance the TOE framework by revealing that

sustainability practices and organizational culture shape adoption within the higher education context. In this way, the adoption decisions become linked not only to technical readiness but also to organizational values. This enhances theoretical frameworks by contextualizing the adoption of AI in universities, recognizing their distinctive socio-educational mission, and emphasizing the need for technology uptake to align with performance in teaching, learning, and research. The study highlights the need for higher learning institutions to boost the quality of AI technologies making them more user-friendly, adaptable, and compatible with contemporary technologies. Intriguingly, for teachers, does this mean utilizing AI tools for developing student-centric learning outcomes for instance through adaptive learning platforms that personalize teaching, automated feedback systems that enable formative assessment and intelligent tutoring systems that enhance curriculum transaction?

Faculty development programs must not only emphasize technical training but also pedagogical integration so that AI tools are integrated into the classroom instead of being a mere add on. The findings suggest that institutional leaders need to create a culture that allows AI creation experiments in classrooms and curriculum design. The universities must embrace AI in MIS and LMS for enhancing TLP through predictive analytics to ensure students' retention, AI-enabled curriculum mapping, digital tools for administrative efficiency and redeployment of faculty time for teaching and research activities. AI adoption requires supportive regulatory policy measures being put into place by policymakers according to the large contribution of Government Regulatory support. It means giving them explicit norms, financial incentives, and training programmes to help them overcome obstacles and adopt AI successfully in their operations. Most importantly, the regulations must encourage the ethical and pedagogically appropriate use of AI in Education. For instance, this can be done through the need for transparency in AI-powered marking, data privacy for students, and curriculum innovation. All these consequences show that AI will be successfully adopted if a three-pronged approach is used by higher education institutions. First, teachers must be equipped with AI-enabled teaching and learning tools. Second, institutional leaders must be enabled to use it in alignment with either strategic performance or curriculum innovation. Finally, lawmakers must provide regulatory frameworks that promote ethics as well as innovation. When these links are made explicit, empirical evidence translates into actions that enhance student learning and teaching and increases institutional competitiveness.

Conclusion

This research examines what drives the adoption of artificial intelligence in Saudi Arabia's tertiary institutions based on the established "Technology-Organisation-Environment (TOE) framework and Diffusion of Innovations (DOI) theory". The study assigns significant weight to Social Trends, Organizational Culture, Sustainability and Waste Management, Compatibility, Relative Advantage, Complexity, and Government Regulatory. This will give a better understanding of the importance of these factors and how they can assist in adopting and successfully using AI. The findings deduce that the Organizational Culture, together with Sustainability and Waste Management are a major determinant of the Social Drivers which impact the influence of several variables on AI adoption by these institutions. Furthermore, the Relative Advantage and Compatibility features are high as the chosen components of Innovation Attributes associated

with AI, which are robust drivers of the intention to use AI-based systems and the actual adoption of their use in practice. In fact, facilitation by government regulations is a strong enabler of the success of AI adoption. In other words, there is a guarantee of success with government regulations. As relevant, mention the contributions of the study for theory building and practical applications. Through the effective contribution of TOE and DOI theories as a comprehensive framework, it enhances our understanding of complexity of AI adoption in higher education. According to the findings, Innovation Attributes and Government Regulatory pressures are significant in the development of the AI adoption process, while the Social Drivers are expected to limit this process. By using evidence to analyse this link, it contributes to the theoretical build-up of technology adoption literature and offers practical implications for organisation engaging in successful implementation of AI technology. The research adds that adopting AI is not just a technical decision; it is a key strategic decision that improves academic quality, enhances administrative efficiency and enables data-driven educational transformation when linked to Technology-Linked Performance (TLP).

Limitations

There are some limitations in the present study that the authors want to highlight. The first limitation is that the research was limited to higher education institutions in Saudi Arabia. As such, the results may not be representative of other cultural, regulatory or institutional settings. Countries that include advanced and emerging economies are facing several barriers to AI adoption. Barriers to AI adoption differ within and between countries. Next, because self-reported survey data were used, the results are vulnerable to various response biases such as social desirability and subjective interpretation of questionnaire items. The third limitation of the present study is its cross-sectional design. Therefore, it provides an instant picture of AI adoption behaviour meant for a point in time. Thereby, it does not capture evolving trends, policy changes, institutional learning, etc. Moreover, the research did not examine other contextual factors beyond the TOE and DOI frameworks. For instance, in countries, the economic conditions or institutional funding variations on rapid technological development may result in AI adoption. Furthermore, while the study's constructs related to innovation category, organisational drivers, and innovation attributes, it did not involve measurements at the teaching, learning or curriculum level. The linking of organisational AI adoption to particular pedagogical practices is limited, as reviewers noted. The gap between institutional-level AI strategies and classroom implementation must be closed in future studies.

Future Recommendations

The above limitations should be addressed by future research where sampling takes place from a larger number of higher educational institutions from different countries and regions. The findings will have greater external validity and cross-cultural applicability. Researchers strongly recommend longitudinal research designs to study how AI adaptation takes place over time as national AI policies mature and institutions accumulate operational experience. Including qualitative methods like interviews and focus groups, and looking at institutional case studies would also help us understand the challenges, barriers and pedagogical changes caused by AI implementation. It is recommended that future studies analyse external factors like economic conditions and technological changes at the national digital transformation level to investigate these strategies. Researchers should particularly analyse how the borrowing of AI by the

organisations impacts teaching quality, curriculum design, assessment innovations and student learning. Examining how leadership, professional development and change management practices help universities to scale AI conduct sustainably and ethically can further enhance future practical guidance.

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