Journal of Information Systems Engineering and Management
2024, 9(2), 23912
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Optimizing Management and Service Systems in Higher Education: A Quantitative Examination of Data Imaging, Interaction Systems, and Decision Support for Informed Decision-Making and Performance Enhancement

Qing Li [1*], Chuming Ren [2]

[1] Lecturer, International College, Krirk University, Bangkok, Thailand
[2] Professor, International College, Krirk University, Bangkok, Thailand
* **Corresponding Author:** 13769061328@163.com

Citation: Li, Q., & Ren, C. (2024). Optimizing Management and Service Systems in Higher Education: A Quantitative Examination of Data Imaging, Interaction Systems, and Decision Support for Informed Decision-Making and Performance Enhancement. *Journal of Information Systems Engineering and Management*, 9(2), 23912.
https://doi.org/10.55267/iadt.07.14677

ARTICLE INFO

Received: 13 Feb 2024
Accepted: 19 Apr 2024

ABSTRACT

Making informed decisions and improving organizational performance are crucial in the modern, data-driven environment. These processes are significantly shaped by a number of variables, including Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, and Technology Readiness. Interaction Systems enable communication and teamwork, Data Imaging translates complex data into visual insights, and Decision Support Systems offer cutting-edge analytics. The IT infrastructure serves as the foundation of technology, and technology readiness measures how ready people and universities are to adopt new technologies. This research aims to explore the interplay between these variables within the context of organizational change theory and their impact on organizational performance and decision-making. Additionally, it examines the moderating effect of Technology Readiness and the mediating role of IT Infrastructure in the organizational change process. Structural Equation Modeling (SEM) in AMOS is used to do this study quantitatively. A total of 450 professionals from various fields are surveyed using reliable questionnaires to compile this data. Within the context of organizational change theory, this study provides insights into the complex interactions between these factors and their combined impact on organizational performance and decision-making. It offers insightful information about how university management can use technology and human resources to improve decision-making procedures and overall performance results. This study adds to both practical and theoretical knowledge, providing concrete recommendations for firms trying to thrive in a technologically driven society. It also increases theoretical understanding by offering a comprehensive framework and putting light on the roles of IT Infrastructure, and Technology Readiness in the decision-making and performance improvement of universities.

Keywords: Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, Technology Readiness, Informed Decision-Making, Performance Enhancement.

INTRODUCTION

In today's corporate environment, making well-informed decisions and improving performance are essential components of success. Making decisions that improve accuracy, reduce risks, and ease strategic planning requires data-driven insights and analysis. S. Lee, Kang, and Kim (2022) say businesses acquire a competitive edge by promoting adaptation and resource efficiency, which increases accountability and ingenuity. However, improving performance simplifies organizational operations, increasing productivity, customer satisfaction, and growth. They boost staff morale, environmental flexibility, sustainability, and profitability. Organizational objectives depend on informed decision-making, which underpins greater performance (Zarghami & Zwikael, 2022). Organizational goal achievement, adaptability, and industry excellence are more likely to succeed and survive. Universities rely on Data Imaging, Interaction, and DSS to increase performance and make educated decisions. Data imaging uses infographics and visuals to simplify data and inform decision-makers. Facilitating data debates, highlighting key patterns or trends, and providing a visual framework for data help data-driven decision making (Benhenneda, Brouard, Charousset, & Berhouet, 2023). Teams can communicate in real time and transparently using interaction systems like communication and collaboration technology. Facilitating stakeholders' access to accurate and timely information, collaborative debates, and data analysis increases informed decision-making. DSS strengthen analytical skills, enabling firms to use data-driven decision-making. DSS helps identify insights from huge databases to improve planning, resource allocation, and operations (Dev, Shankar, & Swami, 2020). These technologies streamline procedures, inspire innovation, promote data-driven cultures, and optimize resource allocation, improving corporate performance. Data Imaging, Interaction Systems, and DSS establish a solid framework for academic success and informed decision-making.

Information technology infrastructure and technical preparation affect universities' decision-making and performance. IT infrastructure underpins data storage, accessibility, and security. It speeds up informed decision-making by providing timely data (Song, Diessner, Ashcraft, & Mo, 2021). IT infrastructure also makes data analytics and collaborative tools work smoothly, giving decision-makers specialized knowledge and data-driven skills (Ninan, Hertogh, & Liu, 2022). IT infrastructure's impact depends on an organization's technological readiness, or competence and determination to use technology. IT infrastructure and technology can help a tech-savvy company or workforce make strategic decisions (Argyroudis et al., 2022). In contrast, a lack of technological readiness may limit the use of IT infrastructure. Data Imaging, Decision Support Systems, Data Imaging, and Technology Readiness have been studied individually on decision-making and performance improvement, but there is no comprehensive analysis of how they interact within a holistic framework. These factors have been studied separately, but how they interact and affect performance and decision-making has not been (Hunte, McCormick, Shah, Lau, & Jang, 2021). There is a scant study on how technological preparation and IT infrastructure moderate these correlations. Today's technologically advanced business world requires understanding these aspects' combined effects and the processes that enable informed decision-making and performance improvement (Greenwood et al., 2022). Filling this research vacuum will give companies looking to improve performance and decision-making a more complete picture.

The aim of this study is to comprehensively examine the interplay of Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, and Technology Readiness in influencing informed decision-making and performance enhancement within organizations. The objectives of the study are as follows:

1. To investigate the individual impacts of Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, and Technology Readiness on informed decision-making and performance enhancement

2. To assess the mediating role of IT Infrastructure in the relationship between Data Imaging, Interaction Systems, Decision Support Systems, and both informed decision-making and performance enhancement.

3. To examine the moderating role of Technology Readiness in the relationship between IT Infrastructure and both informed decision-making and performance enhancement

4. To provide practical recommendations and guidelines for universities based on the study's findings, facilitating more effective decision processes and improved performance outcomes.

This research has major corporate and intellectual consequences. Examining the complex relationships between Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, and Technology Readiness helps universities improve performance and make informed decisions. The findings may change decision-making by giving firms the knowledge they need to make better educated, data-driven decisions in today's complicated and fast-paced corporate world. Optimizing resource allocation, operational processes, and strategic planning can boost performance using the study's conclusions. Understanding Technology Readiness's moderating effects allows firms to tailor technology adoption tactics to their workforce's readiness levels, streamlining and improving technology integration. This research can increase scholarly conversation across disciplines by improving our understanding of technology-human interactions that affect organizational performance and decision-making. Finally, this study's practical recommendations can help university administration improve organizational performance and gain a competitive edge.

LITERATURE REVIEW

Data Imaging and Informed Decision-making

Data imaging means using visual or graphical representations to present data, an important part of information technology that has received attention for informed decision-making. According to Priester et al. (2023), a photograph's greatest value is that it makes us perceive unexpected things. Data imaging uses graphs, charts, and dashboards to simplify complex datasets and improve cognition. The human brain processes visual data naturally, making it better at identifying patterns, trends, and outliers (Ree et al., 2021). Decision-makers benefit from this cognitive advantage, which improves information comprehension and processing. Data imaging impacts decision-making speed and quality beyond visualization. A. Chen, Zhu, Zang, Ding, and Zhan (2019) report that well-designed data visualizations help decision-makers get insights faster and make better decisions. According to D. Kollias, Arsenos, and S. Kollias (2023), an engaging data graphic can convey a lot of information in a short period and with minimal ink in the smallest space. Healthcare, emergency response, and financial trading require immediate decision-making; therefore, efficacy is crucial (Y. T. Chou et al., 2023). Data imaging facilitates collaboration by providing clarity and understanding of complex information, enabling stakeholders to identify patterns and trends, and promoting evidence-based decision-making and transparent communication among organizational stakeholders. Data visualizations let different teams share data-driven insights and make decisions together (Lex et al., 2019). Complex data can be visualized to minimize cognitive load and aid collaborative sense-making.

H1: Data Imaging has a significant and positive impact on Informed Decision Making

Data Imaging and Performance Enhancement

Data visualization using heatmaps, graphs, and charts reveals relationships, anomalies, and trends. This lets decision-makers act fast and wisely. Data imaging also fosters a data-focused culture, which improves performance (J. Liu e, Stewart, Wiens, Mcnitt-Gray, & B. Liu, 2022). Improving data presentation's visual appeal and clarity helps firm stakeholders grasp it. This accessibility helps explore data, make data-driven decisions, and improve performance, according to Somasekar et al. (2019) and Singh et al. (2023) argue that providing better data access can help companies streamline processes, find cost-saving opportunities, and improve performance. Data imaging aids communication and collaboration within a company by visually presenting complex data in an easily understandable format, fostering shared understanding among stakeholders, facilitating discussions based on evidence rather than opinions, and enabling remote teams to collaborate effectively.

H2: Data Imaging has a significant and positive impact on Performance Enhancement

Interaction System and Informed Decision-making

Interaction systems that include organizational change theory and transformational growth affect informed judgments (Vilda, Yagüe Fabra, & Torrents, 2019). The indicated systems use platforms and technology to encourage teamwork and cross-functional communication, representing the key premise of applied university expansion (Veluchamy, Mahesh, Bharathi A., & Sheeba, 2023). Businesses need a thorough requirements evaluation before transforming systems. Key stakeholders must be involved and organizational change theory applied (Barcelona, Castelli, Duncan Cance, Pitt Barnes, & Lee, 2021). This method identifies particular areas for decision-making improvement, analogous to transformational advancement's continuous improvement (Bolton, Raven, & Mintrom, 2021). Interactive communication technologies like real-time texting and video conferencing enable synchronous communication, according to organizational change theory. In crisis management, this is crucial (H. Liu, Lin, & Zhang, 2017). In keeping with the data-driven approach to transformative development, data analytics technologies are needed to monitor and analyze decision-making processes (Ebel, Jaspert, & Poeppelbuss, 2022). According to Zhu and Li's (2023) organizational change theory, honest communication and a collaborative culture that encourages informed decision-making are essential to the transformation strategy. This holistic method uses organizational change theory, transformational development, and applied university development to help organizations improve, make better decisions, and adapt to changing university contexts.

H3: Interaction System has a significant and positive impact on Informed Decision Making

Interaction System and Performance Enhancement

Knowledge sharing and transmission are essential to enhancing interaction systems. These strategies inspire people to percentage explicit and tacit information, improving commercial enterprise intelligence. Employees foster a subculture of chronic studying through participating in collaborative discussions, sharing understanding, and giving feedback through interactive platforms. Together, those movements enhance overall performance (B. J. Lee, 2022). Interactive systems growth group of workers participation and engagement. Interactive equipment can deliver humans with exceptional abilities and viewpoints together for digital cooperation (Wang et al., 2020). Diverse groups are much more likely to resolve problems and make decisions creatively, enhancing overall performance. In addition, interactive communication technology and actual-time collaboration systems assist in accelerating decision-making (Taherdoost & Madanchian, 2022). Staff collaboration and verbal exchange speed up trouble-solving and opportunity-taking, which is important in converting sectors and places of work.

H4: Interaction System has a significant and positive impact on Performance Enhancement

Decision Support System and Informed Decision-making

Institutions increasingly understand the cost of DSS for knowledgeable decision-making. These systems deliver decision-makers quite a few records, analytical equipment, and modeling capabilities, boosting their capacity to make intelligent decisions, according to Davidson (2022). DSS simplifies facts evaluation and can manipulate sizable quantities of statistics, offer beneficial insights, and present data in visual displays and graphs (Kucuksari, Pamucar, Deveci, Erdogan, & Delen, 2023). This functionality streamlines choice-making by way of lowering facts training and evaluation time. DSS can also enhance facts sharing and collaboration inside choice-making groups (Song et al., 2021). DSS allows human beings to conveniently access and compare facts in a consolidated way, allowing conversations and fact-based knowledge.

H5: Decision Support System has a significant and positive impact on Informed Decision Making

Decision Support System and Performance Enhancement

Decision support systems improve organizational performance and informed decision-making. These systems boost operational performance and effectiveness in numerous methods. DSS optimizes resources for overall performance. DSSs control inventories, optimize supply chains, and finances to help enterprises allocate resources (Raei, Reza Alizadeh, Reza Nikoo, & Adamowski, 2019). Data-pushed useful resource allocation saved fees and multiplied efficiency. Additionally, DSS increases remarks and choice-making. Real-time information integration and reporting allow groups to assess and change their sports (Luo, Xu, Aldosari, Althubiti, & Deebani, 2022). Dynamics that need agility and variation advantage from this skill. DSS aggressive intelligence, situation making plans, and trend evaluation raise lengthy-term overall performance (Steininger & Gatzemeier, 2019). Companies that use DSS to make strategic decisions can perceive increase opportunities and respond to marketplace adjustments.

H6: Decision Support System has a significant and positive impact on Performance Enhancement

Underpinning Theory

LaForett and De Marco (2020) uses organizational change theory to understand and manage big enterprise transformation processes. It shows institutional change and advancement. Organizational change theory provides a framework for link analysis (Struckell, Ojha, Patel, & Dhir, 2022). The research on Decision Support Systems, Interaction Systems, and Data Imaging's influence on performance and decision-making supports organizational change theory. Organizational change theory posits that data imaging enhances informed decision-making by providing visual clarity and evidence-based insights, thereby aligning stakeholders and fostering a culture of data-driven decision-making. Organizational transformation encourages data-driven decision-making because data is necessary for change programs (Xie, Wu, Palacios-Marqués, & Ribeiro-Navarrete, 2022). Data visualization helps businesses share and comprehend complex data. Islam, Furuoka, and Idris (2021) argue that informed decision-making causes transformation. Data analysis aids choice. Using data imaging to make educated decisions improves procedures and performance. This supports the theory's goal of improving organizational outcomes through change. Organizational change theory supports the link between interactive systems and performance improvement and informed decision-making (Atadil & Green, 2020). The strategy emphasizes collaboration and communication during transition. Organizational collaboration and communication depend on interaction systems. Interaction technologies improve communication, allowing stakeholders in the change effort to share information and perspectives. These actions support the theory's central idea that well-informed judgments are essential for organizational change. Customized and decision support system-informed decisions improve resource allocation, decision quality, and operational efficiency. This optimization supports the theory's main goal of improving change project results through decision-making (Fix, Rikkerink, Ritzen, Pieters, & Kuiper, 2021).

IT Infrastructure as a Mediator

Informed decision-making is greatly influenced by the way data is presented or represented. IT infrastructure mediation is important. IT infrastructure affects data imaging system availability, dependability, and scalability.

Caldwell (2020) claims that solid IT infrastructure allows data imaging systems to manage massive amounts of data and provide decision-makers with fast access. Data integrity and decision-making confidence are essential. Data protection and governance require it, according to Anejionu et al. (2019). The IT infrastructure must mediate data imaging and well-informed decision-making to give decision-makers quick and reliable access to visible data. The performance benefits of data imaging and IT infrastructure are similar. Data imaging depends on IT infrastructure (Renzi & Trifarò, 2023). Data imaging solutions run smoothly, decrease delay, and allow real-time data viewing with an effective IT architecture. Data imaging systems' ability to manage growing data quantities and user demands depends on the organization's IT infrastructure (Blanquer et al., 2020). Data imaging performance depends on IT infrastructure's strong and adaptable technological architecture. Effective communication and cooperation channels affect informed judgment. However, the IT infrastructure is essential to this association's activities. IT infrastructure affects collaboration platform responsiveness and reliability. Well-maintained IT infrastructure minimizes collaboration disruptions (Argyroudis et al., 2022). The system integrates data from multiple interaction systems, giving decision-makers current information from a variety of sources. The integration and stability of the communication environment, supported by IT infrastructure, affect how interaction systems affect decision-making. Interaction systems improve company productivity through IT infrastructure mediation. A resilient IT infrastructure guarantees an interaction system's stability and scalability, enabling worker collaboration and communication (Villalón-Fonseca, 2022). This capability helps organizations maximize the benefits of online collaboration platforms and virtual teams, enhancing resource allocation and operations. IT infrastructure is also essential for data protection, especially sensitive data (Bernard Bracy, Bao, & Mundy, 2019). Information technology infrastructure increases facilitator performance with interaction systems. DSS help make educated judgments with analytical tools. The mediation function of IT infrastructure is crucial here. The IT infrastructure impacts DSS availability and dependability. Decision help offerings techniques and examine statistics faster with a nicely-organized IT structure. IT infrastructure protects statistics storage and retrieval, ensuring data integrity and decreasing records loss (Beriro et al., 2022). By providing dependable and fast get admission to to selection-supporting statistics, IT infrastructure mediates DSS and aids knowledgeable selection-making. Resilient IT structure improves DSS scalability and actual-time processing. Organizations can efficiently put into effect choice-assisting generation. IT infrastructure facilitates corporations broaden DSS for strategic planning and overall performance improvement via integrating facts (Mohamad, Zainuddin, Alam, & Kendall, 2017). IT infrastructure protection and statistics management are vital for DSS's overall performance enhancement (Lovell, Watson, & Hiteva, 2022). As an intermediate, IT infrastructure provides the technological underpinning to improve DSS overall performance.

H7: IT infrastructure mediates the relationship between data imaging and informed decision-making

H8: IT infrastructure mediates the relationship between data imaging and performance enhancement

H9: IT infrastructure mediates the relationship between Interaction System and informed decision-making

H10: IT infrastructure mediates the relationship between Interaction System and performance enhancement

H11: IT infrastructure mediates the relationship between Decision Support System and informed decision-making

H12: IT infrastructure mediates the relationship between Decision Support System and performance enhancement

Technology Readiness as a Moderator

The relationship between IT infrastructure and informed decision-making depends critically on technological readiness, which refers to people or organizations' willingness and capacity to adopt and effectively use technology. According to Parasuraman's (2000) research, people or organizations that have a high level of technological readiness are more likely to use IT infrastructure to its maximum potential for well-informed decision-making. Because they are better prepared to do so, new IT tools will integrate more easily into their decision-making processes. High technology readiness encourages a proactive approach to technology adoption, where users actively look for and investigate IT resources that can improve their capacity for decision-making (Venkatesh & Davis, 2000). On the other hand, universities, businesses or people who aren't as tech-savvy may find it difficult to make the most of their IT infrastructure, which could result in underuse and unsatisfactory decision-making. As a result, the relationship between IT infrastructure and informed decision-making is moderated by technology readiness, with higher technology readiness increasing the favorable effects of IT infrastructure on decision quality and efficiency.

H13: Technology readiness moderates the relationship between IT infrastructure and informed decision-making.

H14: Technology readiness moderates the relationship between IT infrastructure and performance enhancement.

Based on the above discussion and literature we have proposed the following conceptual framework as shown in **Figure 1**.

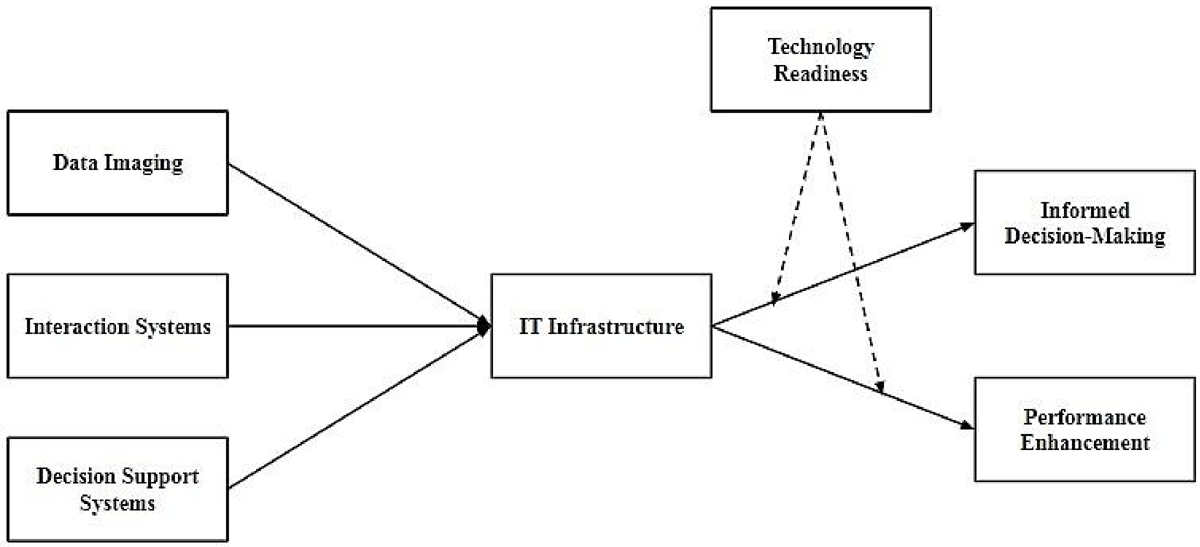

Figure 1. Conceptual Framework

METHODOLOGY

This study employs a quantitative research approach to comprehensively investigate the complex relationships among Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, Technology Readiness, Informed Decision-Making, and Performance Enhancement within organizations. The study relies on a convenience sampling method to gather data from a sample of 450 participants, representing various universities. Primary data is collected through a structured questionnaire, carefully designed to capture the constructs of interest. Validated scales and measurement instruments are used to ensure data reliability and validity. Structural Equation Modeling (SEM) utilizing AMOS software analyzes the data and evaluates the proposed theoretical model. SEM can examine direct and indirect effects, including IT Infrastructure's mediating role and Technology Readiness's moderating influence in its variables' interactions. Model fit indices assess SEM model goodness-of-fit, assuring robust conclusions. The research process is ethical, with informed consent from all participants and strict anonymity and confidentiality precautions. The study protects participants' rights and privacy by following ethical rules.

RESULTS

The data analysis is performed using the software applications Statistical Package for the Social Sciences (SPSS 24) and AMOS 24. **Table 1** shows reliability study results for the variables. Cronbach's Alpha scores show construct internal consistency and reliability. The four-item "Data Imaging" variable has a Cronbach's Alpha rating of 0.871, indicating high internal consistency and reliability. The five-item "Interaction System" variable has a modest Cronbach's Alpha score of 0.702. It still falls within a research-friendly range. With Cronbach's Alphas of 0.784 and 0.768, the four-item "Decision System Support" and three-item "Informed Decision Making" variables are reliable. The four-item "Performance Enhancement" variable has strong internal consistency with a Cronbach's Alpha of 0.803. The five-item "Technology Readiness" variable, with a Cronbach's Alpha of 0.860, is one of the study's most reliable constructs. Last but not least, the four-item variable "IT Infrastructure" has strong dependability with a Cronbach's Alpha of 0.780.

Table 1. Reliability Analysis

Variables	Items	Cronbach's Alpha Value
Data Imaging	4	0.871
Interaction System	5	0.702
Decision System Support	4	0.784
Informed Decision Making	3	0.768
Performance Enhancement	4	0.803
Technology Readiness	5	0.860
IT Infrastructure	4	0.780

For each of the study's variables, **Table 2**'s descriptive statistics reveal the dataset's central tendency and variability. The "N" column shows the consistent sample size of 450 respondents for all variables. The "Mean" column, which displays the average score for each variable, shows that respondents rated "Data Imaging" the highest (4.84), indicating a positive assessment of this feature. The high mean score of 4.73 for "Informed Decision Making" suggests respondents like this topic. "Decision System Support" had a lower mean of 4.09, suggesting less favorability. The "Std. Deviation" column shows answer dispersion around the mean. With 0.927 standard deviation, "Decision System Support" has the most perspectives and possibly the most respondent heterogeneity. However, "Data Imaging" and "Informed Decision Making" show lower standard deviations (0.467 and 0.625, respectively), indicating more consistent responses.

Table 2. Descriptive Statistics

Variables	N	Mean	Std. Deviation
Data Imaging	450	4.84	.467
Interaction System	450	4.66	.688
Decision System Support	450	4.09	.927
It Infrastructure	450	4.59	.642
Informed Decision Making	450	4.73	.625
Technology Readiness	450	4.29	.883
Performance Enhancement	450	4.30	.808

Confirmatory Factor Analysis

The most recent and trustworthy method is pooled confirmatory factor analysis (CFA) (**Figure 2**). All latent variables are processed simultaneously in this manner using the AMOS 24. **Table 3** displays analysis results using RMSEA, CFI, and Chi-Square split by degrees of freedom (Chisq/df) fit indices. Absolute Fit RMSEA is 0.130. Although greater than Breyton, Smith, Rouquette, and Mancini's (2021) threshold of 0.080, this number is acceptable. In terms of incremental fit, the Comparative Fit Index (CFI) yields 0.982, significantly greater than Gundogan's (2022) cutoff point of 0.90. The suggested model matches the facts. Finally, Parsimonious Fit is assessed using the Chi Square to Degrees of Freedom ratio (Chisq/df), 1.932. According to Duffy et al. (2017), this number is below 3, indicating that the model fits well and depicts the relationships without adding complexity.

Table 3. Pooled CFA Model Fitness Tests

Name of Category	Name of Index	Index Full Name	Value in Analysis	Acceptable Value	Literature
Absolute Fit	RMSEA	Root Mean Square of Error Approximation	0.130	<0.80	(Breyton et al., 2021)
Incremental Fit	CFI	Comparative fit index	0.982	>0.90	(Gundogan, 2022)
Parsimonious Fit	Chisq/df	Chi Square / Degrees of freedom	1.932	<3	(Duffy et al., 2017)

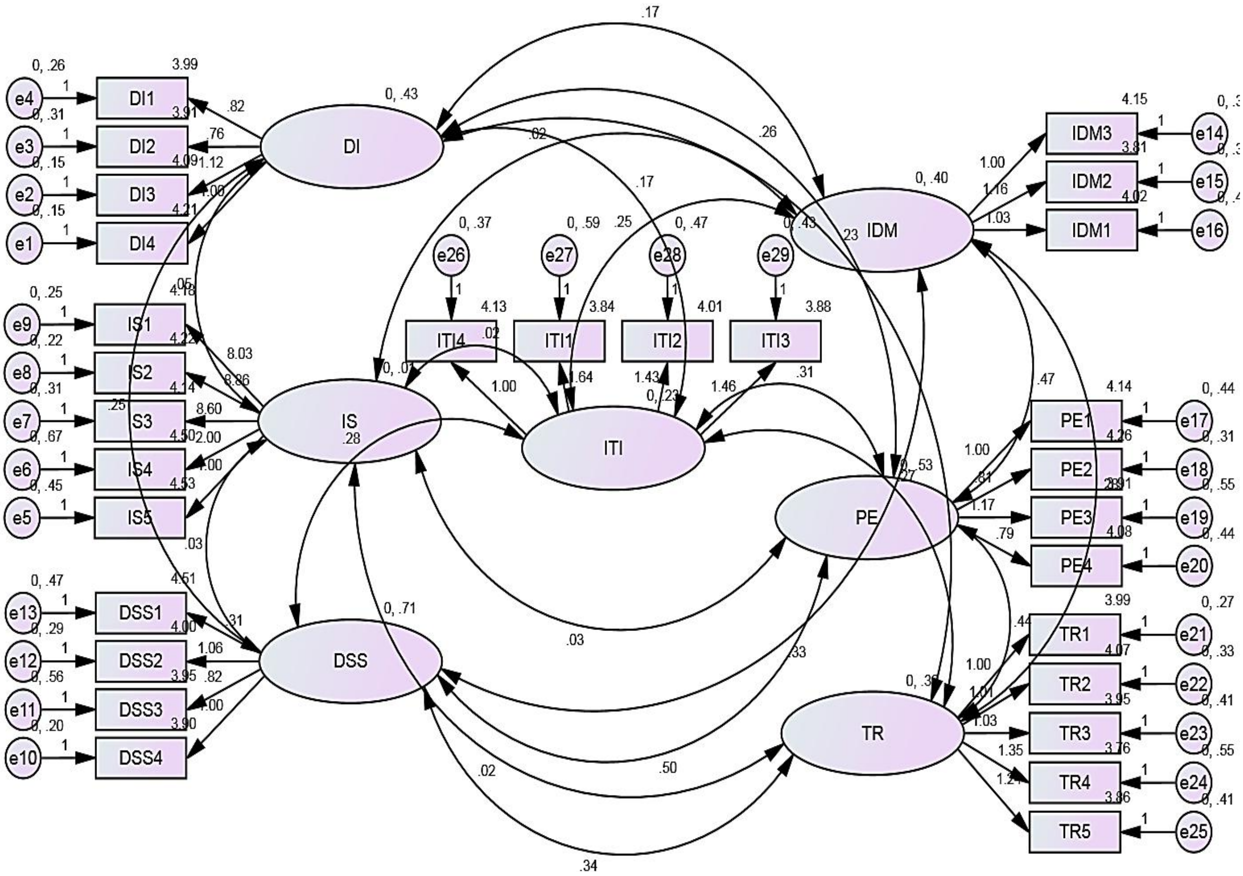

Figure 2. Pooled Confirmatory Factor Analysis (CFA)

The reliability coefficients (Cronbach's Alpha) are shown in **Table 4** for each of the study's variables, providing details on the internal consistency of the assessment items for each variable. These coefficients show how well the items capture the constructions. The "Data Imaging" variable has a high reliability value of 0.871, indicating that its four items reliably and consistently measure the concept. "Decision System Support", "Informed Decision Making", and "Performance Enhancement" variables likewise have good to high reliability, measuring their constructs accurately with coefficients of 0.784, 0.768, and 0.803. The "Technology Readiness" variable stands out and promotes assessment consistency across its five components with a reliability rating of 0.860. Internal consistency is high for the "IT Infrastructure" variable, which has a dependability coefficient of 0.780. The robustness of the measuring scales utilized in the study is highlighted by these reliability coefficients together, providing assurance that the data acquired are valid for further analysis and interpretation.

Table 4. Factor Analysis

Variables	Items	Loading	Reliability
Data Imaging	DI1	0.683	0.871
	DI2	0.584	
	DI3	0.838	
	DI4	0.804	
Interaction System	IS1	0.733	0.702
	IS2	0.774	
	IS3	0.689	
	IS4	0.743	
	IS5	0.827	
Decision System Support	DSS1	0.780	0.784
	DSS2	0.818	
	DSS3	0.631	
	DSS4	0.831	
Informed Decision Making	IDM1	0.663	0.768
	IDM2	0.576	
	IDM3	0.789	

Variables	Items	Loading	Reliability
Performance Enhancement	PE1	0.702	0.803
	PE2	0.775	
	PE3	0.713	
	PE4	0.803	
Technology Readiness	TR1	0.622	0.860
	TR2	0.724	
	TR3	0.582	
	TR4	0.641	
	TR5	0.700	
IT Infrastructure	ITI1	0.779	0.780
	ITI2	0.618	
	ITI3	0.632	
	ITI4	0.608	

Path Analysis in Structural Equation Modelling

This study uses Structural Equation Modeling (SEM) to assess the proposed correlations. To make it simpler to evaluate endogenous factors with AMOS 24, exogenous variables are employed in this analysis. A series of Model Fitness Tests that assess the suitability of the Structural Equation Model (SEM) employed in the study are shown in **Table 5**. There are three types of tests that fall under this heading: absolute fit, incremental fit, and parsimonious fit. The Root Mean Square of Error Approximation (RMSEA) shows a value of 0.466 in terms of Absolute Fit. Although this result above the common criterion of 0.80, as advised by Breyton et al. (2021), it indicates that there is some space for model fit improvement. Moving on to Incremental Fit, the Comparative Fit Index (CFI) is calculated and returns a score of 0.921, which is greater than the 0.90 acceptable level indicated by Gundogan (2022). This suggests a reasonably excellent match between the suggested SEM and the data, especially when Incremental fit indices are considered. Last but not least, the Chi Square to Degrees of Freedom ratio (Chisq/df) in the Parsimonious Fit category calculates to 1.762, which is below the advised threshold of 3 according to Duffy et al. (2017). By capturing the underlying relationships without adding unnecessary complexity, the model is said to achieve a parsimonious fit.

Table 5. SEM, Model Fitness Tests

Name of Category	Name of Index	Index Full Name	Value in Analysis	Acceptable Value	Literature
Absolute Fit	RMSEA	Root Mean Square of Error Approximation	0.466	< 0.80	(Breyton et al., 2021)
Incremental Fit	CFI	Comparative fit index	0.921	> 0.90	(Gundogan, 2022)
Parsimonious Fit	Chisq/df	Chi Square / Degrees of freedom	1.762	< 3	(Duffy et al., 2017)

Structural Model

Table 6 and **Figure 3** show the study's direct impacts, which examine how particular factors affect other components. H1–H6 each represent a causal path and have a standardized estimated effect, T-value, and P-value indicating significance. H1 indicates a positive connection between DI and IDM with a significant standardized estimate of 0.660 and T-value of 12.00. Data imaging improves informed decision making, according to this result. The results support the H2 hypothesis that DI and PE are positively correlated with a standardized estimate of 0.109, a T-value of 2.230, and a P-value of 0.026. Though weaker than H1, DI has a statistically significant effect on Performance Enhancement. H3 found a substantial positive correlation between IS and IDM with a standardized estimate of 0.339 and a high T-value of 14.560. Thus, a good Interaction System aids Informed Decision Making. H4's study on IS and PE found a positive effect, supported by a standardized estimate of 0.097, a T-value of 2.933, and a P-value of 0.004. Interaction System has a tiny but statistically significant effect on Performance Enhancement. H5 finds a positive connection between DSS and IDM with a standardized estimate of 0.134 and a T-value of 4.290, showing that good DSS assists Informed Decision Making. The results of H6's assessment of the link between DSS and PE show a favorable effect, which is supported by a standardized estimate of 0.108, a T-value of 4.458, and a P-value of 0.001. This shows that Performance Enhancement is statistically influenced by an effective Decision System Support as well.

Table 6. Results of Direct Effects

Hypothesis	Causal Path	Standardized Estimated	T Value	P-Value
H1	DI -> IDM	0.660	12.00	0.001
H2	DI -> PE	0.109	2.230	0.026
H3	IS -> IDM	0.339	14.560	0.001
H4	IS -> PE	0.097	2.933	0.004
H5	DSS -> IDM	0.134	4.290	0.001
H6	DSS -> PE	0.108	4.458	0.001

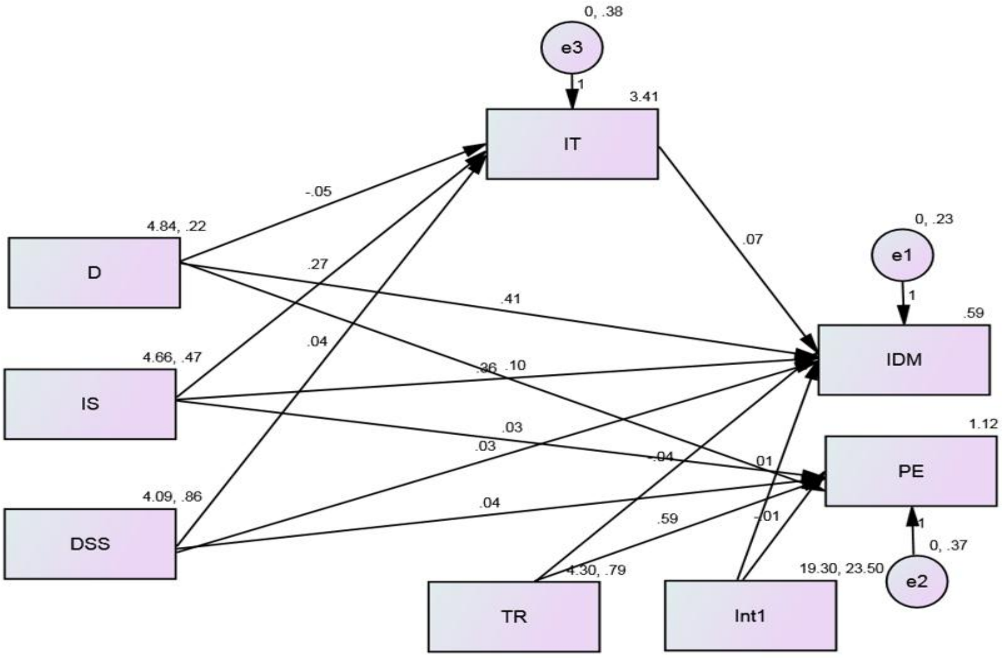

Figure 3. Structural Model

Mediation Analysis

Table 7 shows the findings of mediation studies, which investigate the indirect effects of factors on constructs in the research through an intermediate variable ITI. With an original sample coefficient of 0.157, a T-value of 4.856, and a P-value of 0.001, the hypothesis H7 demonstrates a substantial mediation effect. This shows that ITI, through DI, indirectly influences IDM. With an original sample coefficient of 0.123, a T-value of 4.995, and a P-value of 0.001, hypothesis H8 likewise displays a significant mediation effect. This suggests that through ITI, SM indirectly affects IDM. Furthermore, with an original sample coefficient of 0.269, a T-value of 6.369, and a P-value of 0.001, the hypothesis H9 shows a substantial mediation effect. This shows DSS indirectly affects IDM via ITI. With a 0.026 original sample coefficient, 2.051 T-value, and 0.040 P-value, hypothesis H10 shows a substantial mediation effect. This shows DI indirectly affects PE through ITI. Hypothesis H11 shows a significant mediation effect with an original sample coefficient of 0.088, T-value of 2.725, and P-value of 0.007. ITI implies that SM indirectly affects PE. Finally, hypothesis H12 has a significant mediation effect with an original sample coefficient of 0.129, a T-value of 1.999, and a P-value of 0.046. So DSS indirectly influences PE through ITI.

Table 7. Results of Mediation

Hypothesis	Original Sample	T Values	P Values
DI -> ITI -> IDM	0.157	4.856	0.001
DI -> ITI -> PE	0.026	2.051	0.040
SM -> ITI -> IDM	0.123	4.995	0.001
SM -> ITI -> PE	0.088	2.725	0.007
DSS -> ITI -> IDM	0.269	6.369	0.001
DSS -> ITI -> PE	0.129	1.999	0.046

Moderation Analysis

Table 8 shows mediation analyses of ITI and TR interactions and their effects on IDM and PE. Hypothesis H13 shows a significant interaction effect with an original sample coefficient of 0.224, a T-value of 4.654, and a P-value of 0.001. The combined effects of ITI and TR appear to significantly affect IDM. Hypothesis H14 shows a significant interaction effect with an original sample coefficient of 0.011, a T-value of 2.051, and a P-value of 0.041. This shows ITI and TR's combined impact on PE is significant.

Table 8. Results of Mediation

Hypothesis	Original Sample	T Values	P Values
ITI * TR -> IDM	0.224	4.654	0.001
ITI * TR -> PE	0.011	2.051	0.041

DISCUSSION

Informed decision-making is significantly and favorably impacted by the application of data imaging, according to Hypothesis 1. Several important variables make data visualization improve informed decision-making. Data visualization tools like heatmaps, graphs, and charts help decision-makers visualize complex data sets (Hu et al., 2022). This visualization of complex data helps decision-makers spot repeated patterns, anomalies, and linkages (Alkosha et al., 2022). Data imaging increases data availability to more business employees. Interactive dashboards may democratize data by making it visually beautiful and understandable. Decision-makers from diverse departments and skill levels can readily access and assess data using these dashboards (Hoelscher & Mortimer, 2018). According to our study participants, data availability helps investigation and conclusion-making. Hypothesis 2 predicts that data imaging will significantly improve performance. Data imaging boosts performance in several ways. Data visualization helps organizations gain valuable insights from their data (Pratt, Bisson, & Warin, 2023). Faster and more informed decision-making from accelerated data understanding helps organizations become more agile and effective. Data imaging improved procedure efficiency and performance, according to study participants. Data visualization improves data-driven organizational collaboration (Wu et al., 2021). Visualized data encourages teamwork and creativity by enabling communication, discussion, and participation. A cooperative environment often reveals ways to improve performance and optimize procedures (Shamim, Zeng, Khan, & Zi, 2020). Data imaging also helps companies identify bottlenecks and growth opportunities. Raw data may not reveal outliers and trends, but visual data does (Liao, He, X. Wu, Z. Wu, & Bausys, 2023). This data helps organizations enhance their products and services, maximize resource allocation, and react to changing market conditions.

Hypothesis 3 implies that interaction structures substantially improve knowledgeable choice-making. Interactive structures permit knowledge sharing and teamwork (Yun, Ma, & Yang, 2021). Ahmad, Bahri, and Fauzi (2023) mentioned that those tools permit file sharing, real-time verbal exchange, and digital conferences, which enhance choice-making by generating informed discourse. To make informed judgments, you want quick get right of entry to to statistics and the potential to evaluate alternatives. Yu, Jin, Cai, Zhao, and Zhang (2022) say interplay structures growth organizational transparency. By fostering open discourse and data-pushed choice making, interplay systems give selection-makers access to all relevant information. Hypothesis 4 argues that interaction structures drastically improve overall performance. Team overall performance improves with interplay systems' collaboration and communication. These structures' collaborative workspaces and real-time cooperation help accelerate decision-making (C. M. Chen, Li, & T. C. Chen, 2020). Interaction era assist institutions engage digital groups and sell remote work. This lets institutions recruit greater talented applicants and enhance useful resource control. Staff collaboration and verbal exchange speed up trouble-solving and opportunity-taking, which is important in converting sectors and places of work.

Hypothesis 5 argues that DSS improve informed decision-making. Decision-makers can model and analyze data with the DSS. Decision-makers need these skills to examine scenarios and predict outcomes (Senocak & Guner Goren, 2023). Decision-makers also receive instant data from the DSS. Jacobsson, Arnäs, and Stefansson (2020) say real-time data speeds decision-making. Quickly changing business scenarios require timely information for educated decision-making. DSS improve decision-making by outsourcing calculations and repetitive chores (Vink, 2022). Automation enhanced decision-making by letting people focus on strategic aspects, reducing errors. The 6th hypothesis suggests that DSS significantly improve performance. Through informed decision-making, DSS improves organizational effectiveness. DSS insights affect operation methodologies, resource allocation, and strategy, according to Ramaswamy Govindan and Li (2023). DSS boost organizational performance when used regularly. DSS encourages data-driven optimization (N. Ahmed, Assadi, A. A. Ahmed, & Banihabib, 2023). DSS helped identify performance issues and develop data-driven improvements. Resource allocation and operational efficiency have increased with these advances.

Hypothesis 7 says IT infrastructure affects data imaging and informed decision-making. IT infrastructure provides the foundation for enterprise-wide data imaging, according to Blanquer et al. (2020). The system has the hardware, software, and networking needed for data imaging applications. Chou and Ongkowijoyo (2019) found that IT infrastructure is essential for data imaging solution implementation and operation. A poor IT infrastructure might hinder data imaging processes, reducing their ability to influence decision-making. Additionally, IT infrastructure ensures data availability and accessibility. Hypothesis 8 states that IT architecture controls data imaging and performance enhancement. Information technology supports data imaging tools and systems. Choi and Park (2022) recognized that data imaging systems need IT infrastructure to run smoothly. Lack of IT infrastructure support may reduce data imaging technologies' capacity to boost company performance. IT infrastructure helps manage, retrieve, and store data. IT infrastructure is essential for storing and retrieving graphical data, according to S. Kierner, Kucharski, and Z. Kierner (2023). This is essential for performance and quick decision-making. Graphical data is easily accessible, speeding up decision-making.

According to Hypotheses 9 and 10, IT infrastructure facilitates the linkages between Interaction Systems and Informed Decision-making and Performance Enhancement. Anthony (2019) hypothesizes that IT infrastructure in Interaction Systems affects organizational performance and decision-making. Interaction Systems' communication and collaboration components depend on IT infrastructure. Fan and Pan (2023) found that IT infrastructure helped interaction systems work well. These systems may fail to increase performance and inform decision-making without a solid IT infrastructure. Interaction systems require data transport and availability, which IT infrastructure provides (Mushore & Kyobe, 2022). IT enables real-time communication, document collaboration, and virtual meetings, which encourage logical decision-making. These qualities also boost productivity by encouraging teamwork. IT infrastructure may affect DSS and Informed Decision-making and Performance Enhancement, according to Hypotheses 11 and 12. These theories suggest that DSS employ IT infrastructure to enable data-driven decision-making and increase organizational performance. Joshi, Benitez, Huygh, Ruiz, and De Haes (2022) say DSS provides data modeling and analysis hardware and software. Our research participants understood the relevance of IT infrastructure for DSS smoothness. DSS may struggle to assist informed decision-making and increase performance without a strong IT infrastructure. IT infrastructure ensures data confidentiality, accessibility, and availability, which boosts DSS efficiency (Hajializadeh & Imani, 2021). Large datasets can be stored and accessed via IT infrastructure for data-driven decisions. IT infrastructure helps secure data, which is vital to data confidentiality and integrity. DSS users need data assurance.

Technological preparation moderates the relationship between IT infrastructure and Informed Decision-making and Performance Enhancement, according to Hypotheses 13 and 14. These notions suggest that IT infrastructure may affect decision-making and performance for people and organizations with different technological readiness levels. Technology readiness measures an individual or organization's technology acceptance and use (Mahroof, 2019). Tengilimoglu, Carsten, and Wadud (2023) found that certain people were more tech-savvy than others. Technically savvy people and companies may use IT infrastructure to make better decisions. Salim, El Barachi, Mohamed, Halstead, and Babreak (2022) said IT infrastructure makes them easier in adopting new tools and processes. Those without technological skills may struggle to adapt, preventing them from fully utilizing IT infrastructure in decision-making. Preparing for technology can limit IT infrastructure's performance-boosting effects. High technical readiness helps integrate and use performance-enhancing technologies and procedures supported by IT infrastructure (Hasan, Ali, Kurnia, & Thurasamy, 2021). Limited technological expertise may make it difficult for people to accept new technology, limiting how much IT infrastructure can improve performance.

CONCLUSION

The complicated network of factors that increase university administration performance and decision-making was explored in this study. Technology Readiness, Data Imaging, Interaction Systems, Decision Support Systems, and IT Infrastructure have been studied in relation to the organizational environment. Data Imaging and Decision Support Systems enable data-driven decision-making, as shown by our findings. These tools allow university management to gain insights from large databases and provide recommendations for operational operations, resource allocation, and strategic planning. The research also shows that interaction systems improve cooperation, transparency, data-driven cultures, and organizational effectiveness. IT infrastructure underpins various technologies, ensuring data availability, expandability, and security. This study explored how Technology Readiness influences IT Infrastructure, performance, and informed decision-making. Our research illuminated these processes' mechanics. The research can boost organizational performance and decision-making. The study offers practical guidance for combining technological skills with human preparedness to prepare university administration for digital change. This study provides a multifaceted paradigm for how IT Infrastructure and Technology Readiness increase performance and decision-making.

IMPLICATIONS

This study's findings can help university management improve decision-making and performance. The document contains detailed instructions for implementing Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, and Technology Readiness. These insights help organizations make data-driven decisions. This capacity helps companies improve strategic decision-making, resource allocation, and operational results. The study's focus on technological readiness can help organizations create training programs that fully equip employees to use technology. These notions help organizations respond to market changes more effectively, giving them a competitive edge. The study's theoretical implications benefit academia. The framework is comprehensive and considers numerous factors that affect decision-making and performance. The study also shows how IT infrastructure mediates and technological preparedness moderates the complex interplay between technology and human variables in universities and enterprises. This comprehensive view emphasizes the importance of technology and human aspects in theoretical frameworks. This study shows how theoretical ideas are applied in organizations, emphasizing the importance of theory-practice integration.

LIMITATIONS

This study provides essential information regarding how Data Imaging, Interaction Systems, Decision Support Systems, IT Infrastructure, and Technology Readiness interact to influence well-informed decision-making and performance improvement, but its limits must be acknowledged. First, the study's findings may not apply to any industry or organizational design. The study also uses self-reported data, which may be biased and inaccurate. Over time, these components may change, but the study only considers their impact at one time. Finally, the study ignores contextual and confounding elements that may affect decision-making and performance.

FUTURE DIRECTIONS

This study outlines interesting future research directions. Future research could encompass new industries. This would help explain these qualities' activity across sectors. Long-term connections can be studied in response to organizational dynamics and technology contexts. Qualitative research methods like interviews and case studies help explain how the study's recommendations might be applied in organizations. Additionally, analyzing leadership attributes and organizational culture may help us comprehend the complex processes that affect performance and decision-making. Comparison evaluations between areas or countries may indicate how cultural factors affect technological acceptability and preparedness, providing significant cross-cultural insights.

CONFLICT OF INTEREST

No potential conflict of interest was reported by the authors.

REFERENCES

Ahmad, N. S., Bahri, S., & Fauzi, A. (2023). Does Mobile Instant Messaging (MIM) affect power redistribution? Evidence from a Malaysian school management organization. *Social Sciences & Humanities Open*, *7*(1), 100495.

Ahmed, N., Assadi, M., Ahmed, A. A., & Banihabib, R. (2023). Optimal design, operational controls, and data-driven machine learning in sustainable borehole heat exchanger coupled heat pumps: Key implementation challenges and advancement opportunities. *Energy for Sustainable Development*, *74*, 231-257.

Alkosha, H. M. A., El Adalany, M. A., Elsobky, H., Zidan, A. S., Sabry, A., & Awad, B. I. (2022). Flexion/Extension cervical magnetic resonance imaging: A potentially useful tool for decision-making in patients with symptomatic degenerative cervical spine. *World Neurosurgery*, *164*, e1078-e1086.

Anejionu, O. C. D., Thakuriah, P. (Vonu), McHugh, A., Sun, Y., McArthur, D., Mason, P., & Walpole, R. (2019). Spatial urban data system: A cloud-enabled big data infrastructure for social and economic urban analytics. *Future Generation Computer Systems*, *98*, 456-473.

Anthony, B. (2019). Green information system integration for environmental performance in organizations: An extension of belief-action-outcome framework and natural resource-based view theory. *Benchmarking*, *26*(3), 1033-1062.

Argyroudis, S. A., Mitoulis, S. A., Chatzi, E., Baker, J. W., Brilakis, I., Gkoumas, K., . . . Linkov, I. (2022). Digital technologies can enhance climate resilience of critical infrastructure. *Climate Risk Management*, *35*, 100387.

Atadil, H. A., & Green, A. J. (2020). An analysis of attitudes towards management during culture shifts. *International Journal of Hospitality Management*, *86*, 102439

Barcelona, J. M., Castelli, D. M., Duncan Cance, J., Pitt Barnes, S., & Lee, S. (2021). Presidential youth fitness program implementation: An antecedent to organizational change. *Evaluation and Program Planning*, *86*. https://doi.org/10.1016/j.evalprogplan.2021.101919

Benhenneda, R., Brouard, T., Charousset, C., & Berhouet, J. (2023). Can artificial intelligence help decision-making in arthroscopy? Part 2: The IA-RTRHO model—A decision-making aid for long head of the biceps diagnoses in small rotator cuff tears. *Orthopaedics & Traumatology: Surgery & Research*, 103652.

Beriro, D., Nathanail, J., Salazar, J., Kingdon, A., Marchant, A., Richardson, S., . . . Nathanail, P. (2022). A decision support system to assess the feasibility of onshore renewable energy infrastructure. *Renewable and Sustainable Energy Reviews*, *168*, 112771.

Bernard Bracy, J. M., Bao, K. Q., & Mundy, R. A. (2019). Highway infrastructure and safety implications of AV technology in the motor carrier industry. *Research in Transportation Economics*, *77*. https://doi.org/10.1016/j.retrec.2019.100758

Blanquer, I., Brasileiro, F., Brito, A., Calatrava, A., Carvalho, A., Fetzer, C., . . . Silva, F. (2020). Federated and secure cloud services for building medical image classifiers on an intercontinental infrastructure. *Future Generation Computer Systems*, *110*, 119-134.

Bolton, M., Raven, R., & Mintrom, M. (2021). Can AI transform public decision-making for sustainable development? An exploration of critical earth system governance questions. *Earth System Governance*, *9*, 100116.

Breyton, M., Smith, A. Ben, Rouquette, A., & Mancini, J. (2021). Cancer information overload: Association between a brief version of the CIO scale and multiple cancer risk management behaviours. *Patient Education and Counseling*, *104*(5), 1246-1252.

Caldwell, M. (2020). An investigation into the perceptions of Japanese University educators on the use of ICT in an EFL tertiary setting. *CALL-EJ*, *21*(2), 1-16.

Chen, A., Zhu, L., Zang, H., Ding, Z., & Zhan, S. (2019). Computer-aided diagnosis and decision-making system for medical data analysis: A case study on prostate MR images. *Journal of Management Science and Engineering*, *4*(4), 266-278.

Chen, C. M., Li, M. C., & Chen, T. C. (2020). A web-based collaborative reading annotation system with gamification mechanisms to improve reading performance. *Computers & Education*, *144*, 103697.

Choi, S. H., & Park, K. W. (2022). Cloud-BlackBox: Toward practical recording and tracking of VM swarms for multifaceted cloud inspection. *Future Generation Computer Systems*, *137*, 219-233.

Chou, J. S., & Ongkowijoyo, C. S. (2019). Hybrid decision-making method for assessing interdependency and priority of critical infrastructure. *International Journal of Disaster Risk Reduction*, *39*, 101134.

Chou, Y. T., Lin, C. T., Chang, T. A., Wu, Y. L., Yu, C. E., Ho, T. Y., . . . Kuang-Sheng Lee, O. (2023). Development of artificial intelligence-based clinical decision support system for diagnosis of meniscal injury using magnetic resonance images. *Biomedical Signal Processing and Control*, *82*, 104523.

Davidson, H. (2022). The Assisted Decision-Making (Capacity) Act 2015: Interrogating the guiding principles for a person with dementia. *International Journal of Law and Psychiatry*, *84*, 101819.

Dev, N. K., Shankar, R., & Swami, S. (2020). Diffusion of green products in industry 4.0: Reverse logistics issues during design of inventory and production planning system. *International Journal of Production Economics*, *223*, 107519.

Duffy, R. D., Allan, B. A., England, J. W., Blustein, D. L., Autin, K. L., Douglass, R. P., . . . Santos, E. J. R. (2017). The development and initial validation of the decent work scale. *Journal of Counseling Psychology*, *64*(2), 206-221.

Ebel, M., Jaspert, D., & Poeppelbuss, J. (2022). Smart already at design time—Pattern-based smart service innovation in manufacturing. *Computers in Industry*, *138*. https://doi.org/10.1016/j.compind.2022.103625

Fan, B., & Pan, T. (2023). Does information technology–organizational resource interaction affect E-government performance? Moderating roles of environmental uncertainty. *Government Information Quarterly*. https://doi.org/10.1016/j.giq.2023.101830

Fix, G. M., Rikkerink, M., Ritzen, H. T. M., Pieters, J. M., & Kuiper, W. A. J. M. (2021). Learning within sustainable educational innovation: An analysis of teachers' perceptions and leadership practice. *Journal of Educational Change*, *22*(1), 131-145.

Greenwood, M., Wrogemann, J. M., Schmuch, R., Jang, H., Winter, M., & Leker, J. (2022). The Battery Component Readiness Level (BC-RL) framework: A technology-specific development framework. *Journal of Power Sources Advances*, *14*. https://doi.org/10.1016/j.powera.2022.100089

Gundogan, S. (2022). The relationship of COVID-19 student stress with school burnout, depression and subjective well-being: Adaptation of the COVID-19 student stress scale into Turkish. *Asia-Pacific Education Researcher*. https://doi.org/10.1007/S40299-021-00641-2

Hajializadeh, D., & Imani, M. (2021). RV-DSS: Towards a resilience and vulnerability-informed decision support system framework for interdependent infrastructure systems. *Computers & Industrial Engineering*, *156*, 107276.

Hasan, S., Ali, M., Kurnia, S., & Thurasamy, R. (2021). Evaluating the cyber security readiness of organizations and its influence on performance. *Journal of Information Security and Applications*, *58*, 102726.

Hoelscher, J., & Mortimer, A. (2018). Using Tableau to visualize data and drive decision-making. *Journal of Accounting Education*, *44*, 49-59.

Hu, A., Chaudhury, A. S., Fisher, T., Garcia, E., Berman, L., Tsao, K., . . . Raval, M. V. (2022). Barriers and facilitators of CT scan reduction in the workup of pediatric appendicitis: A pediatric surgical quality collaborative qualitative study. *Journal of Pediatric Surgery*, *57*(11), 582-588.

Hunte, M. R., McCormick, S., Shah, M., Lau, C., & Jang, E. E. (2021). Investigating the potential of NLP-driven linguistic and acoustic features for predicting human scores of children's oral language proficiency. *Assessment in Education: Principles, Policy and Practice*, *28*(4), 477-505.

Islam, M. N., Furuoka, F., & Idris, A. (2021). Mapping the relationship between transformational leadership, trust in leadership and employee championing behavior during organizational change. *Asia Pacific Management Review*, *26*(2), 95-102.

Jacobsson, S., Arnäs, P. O., & Stefansson, G. (2020). Automatic information exchange between interoperable information systems: Potential improvement of access management in a seaport terminal. *Research in Transportation Business & Management*, *35*, 100429.

Joshi, A., Benitez, J., Huygh, T., Ruiz, L., & De Haes, S. (2022). Impact of IT governance process capability on business performance: Theory and empirical evidence. *Decision Support Systems*, *153*, 113668.

Kierner, S., Kucharski, J., & Kierner, Z. (2023). Taxonomy of hybrid architectures involving rule-based reasoning and machine learning in clinical decision systems: A scoping review. *Journal of Biomedical Informatics*, *144*, 104428.

Kollias, D., Arsenos, A., & Kollias, S. (2023). A deep neural architecture for harmonizing 3-D input data analysis and decision making in medical imaging. *Neurocomputing*, *542*, 126244.

Kucuksari, S., Pamucar, D., Deveci, M., Erdogan, N., & Delen, D. (2023). A new rough ordinal priority-based decision support system for purchasing electric vehicles. *Information Sciences*, *647*, 119443.

LaForett, D. R., & De Marco, A. (2020). A logic model for educator-level intervention research to reduce racial disparities in student suspension and expulsion. *Cultural Diversity and Ethnic Minority Psychology*, *26*(3), 295-305.

Lee, B. J. (2022). Enhancing listening comprehension through kinesthetic rhythm training. *RELC Journal*, *53*(3), 567-581.

Lee, S., Kang, M. J., & Kim, B. K. (2022). Factors influencing entrepreneurial intention: Focusing on individuals' knowledge exploration and exploitation activities. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3). https://doi.org/10.3390/joitmc8030165

Lex, S. W., Calì, D., Koed Rasmussen, M., Bacher, P., Bachalarz, M., & Madsen, H. (2019). A cross-disciplinary path to healthy and energy efficient buildings. *Technological Forecasting and Social Change*, *142*, 273-284.

Liao, H., He, Y., Wu, X., Wu, Z., & Bausys, R. (2023). Reimagining multi-criterion decision making by data-driven methods based on machine learning: A literature review. *Information Fusion*, *100*, 101970.

Liu, H., Lin, C. H., & Zhang, D. (2017). Pedagogical beliefs and attitudes toward information and communication technology: A survey of teachers of English as a foreign language in China. *Computer Assisted Language Learning*, *30*(8), 745-765.

Liu, J., Stewart, H., Wiens, C., Mcnitt-Gray, J., & Liu, B. (2022). Development of an integrated biomechanics informatics system with knowledge discovery and decision support tools for research of injury prevention and performance enhancement. *Computers in Biology and Medicine*, *141*, 105062.

Lovell, K., Watson, J., & Hiteva, R. (2022). Infrastructure decision-making: Opening up governance futures within techno-economic modelling. *Technological Forecasting and Social Change*, *174*, 121208.

Luo, J., Xu, J., Aldosari, O., Althubiti, S. A., & Deebani, W. (2022). Design and implementation of an efficient electronic bank management information system based data warehouse and data mining processing. *Information Processing & Management*, *59*(6), 103086.

Mahroof, K. (2019). A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *International Journal of Information Management*, *45*, 176-190.

Mohamad, A., Zainuddin, Y., Alam, N., & Kendall, G. (2017). Does decentralized decision making increase company performance through its Information Technology infrastructure investment? *International Journal of Accounting Information Systems*, *27*. https://doi.org/10.1016/j.accinf.2017.09.001

Mushore, R., & Kyobe, M. (2022). Aligning tasks, technology, people, and structures to leverage the value of big data analytics. *Procedia Computer Science*, *203*, 739-744.

Ninan, J., Hertogh, M., & Liu, Y. (2022). Educating engineers of the future: T-shaped professionals for managing infrastructure projects. *Project Leadership and Society*, *3*. https://doi.org/10.1016/j.plas.2022.100071

Parasuraman, A. (2000). Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies. *Journal of service research*, *2*(4), 307-320.

Pratt, L., Bisson, C., & Warin, T. (2023). Bringing advanced technology to strategic decision-making: The Decision Intelligence/Data Science (DI/DS) Integration framework. *Futures*, *152*, 103217.

Priester, A., Fan, R. E., Shubert, J., Rusu, M., Vesal, S., Shao, W., . . . Sonn, G. A. (2023). Prediction and mapping of intraprostatic tumor extent with artificial intelligence. *European Urology Open Science*, *54*, 20-27.

Raei, E., Reza Alizadeh, M., Reza Nikoo, M., & Adamowski, J. (2019). Multi-objective decision-making for green infrastructure planning (LID-BMPs) in urban storm water management under uncertainty. *Journal of Hydrology*, *579*, 124091.

Ramaswamy Govindan, A., & Li, X. (2023). Fuzzy logic-based decision support system for automating ergonomics risk assessments. *International Journal of Industrial Ergonomics*, *96*, 103459.

Ree, I. M. C., van 't Oever, R. M., Jansen, L., Lopriore, E., de Haas, M., & van Klink, J. M. M. (2021). School performance and behavioral functioning in children after intrauterine transfusions for hemolytic disease of the fetus and newborn. *Early Human Development*. https://doi.org/10.1016/j.earlhumdev.2021.105381

Renzi, E., & Trifarò, C. A. (2023). Knowledge and Digitalization: A way to improve safety of Road and Highway Infrastructures. *Procedia Structural Integrity*, *44*, 1228-1235.

Salim, T. A., El Barachi, M., Mohamed, A. A. D., Halstead, S., & Babreak, N. (2022). The mediator and moderator roles of perceived cost on the relationship between organizational readiness and the intention to adopt blockchain technology. *Technology in Society*, *71*, 102108.

Senocak, A. A., & Guner Goren, H. (2023). Three-phase artificial intelligence-geographic information systems-based biomass network design approach: A case study in Denizli. *Applied Energy*, *343*. https://doi.org/10.1016/j.apenergy.2023.121214

Shamim, S., Zeng, J., Khan, Z., & Zia, N. U. (2020). Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technological Forecasting and Social Change*, *161*. https://doi.org/10.1016/j.techfore.2020.120315

Singh, S., Singh, H., Bueno, G., Deniz, O., Singh, S., Monga, H., . . . Pedraza, A. (2023). A review of image fusion: Methods, applications and performance metrics. *Digital Signal Processing*, *137*. https://doi.org/10.1016/j.dsp.2023.104020

Somasekar, J., Ramesh, G., Ramu, G., Dileep Kumar Reddy, P., Eswara Reddy, B., & Lai, C. H. (2019). A dataset for automatic contrast enhancement of microscopic malaria infected blood RGB images. *Data in Brief*, *27*. https://doi.org/10.1016/j.dib.2019.104643

Song, C., Diessner, N. L., Ashcraft, C. M., & Mo, W. (2021). Can science-informed, consensus-based stakeholder negotiations achieve optimal dam decision outcomes? *Environmental Development*, *37*. https://doi.org/10.1016/j.envdev.2020.100602

Steininger, D. M., & Gatzemeier, S. (2019). Digitally forecasting new music product success via active crowdsourcing. *Technological Forecasting and Social Change*, *146*, 167-180.

Struckell, E., Ojha, D., Patel, P. C., & Dhir, A. (2022). Strategic choice in times of stagnant growth and uncertainty: An institutional theory and organizational change perspective. *Technological Forecasting and Social Change*, *182*, 121839.

Taherdoost, H., & Madanchian, M. (2022). Employment of technological-based approaches for creative E-learning; Teaching management information systems. *Procedia Computer Science*, *215*, 802-808.

Tengilimoglu, O., Carsten, O., & Wadud, Z. (2023). Infrastructure requirements for the safe operation of automated vehicles: Opinions from experts and stakeholders. *Transport Policy*, *133*, 209-222.

Veluchamy, S., Mahesh, K. M., Bharathi A., P., & Sheeba, P. T. (2023). DeepDrive: A braking decision making approach using optimized GAN and Deep CNN for advanced driver assistance systems. *Engineering Applications of Artificial Intelligence*, *123*. https://doi.org/10.1016/j.engappai.2023.106111

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.

Vilda, F. G., Yagüe Fabra, J. A., & Torrents, A. S. (2019). Person-based design: A human-centered approach for lean factory design. *Procedia Manufacturing*, *41*, 445-452.

Villalón-Fonseca, R. (2022). The nature of security: A conceptual framework for integral-comprehensive modeling of IT security and cybersecurity. *Computers & Security*, *120*. https://doi.org/10.1016/j.cose.2022.102805

Vink, L. S. (2022). A new methodology for assessing human contributions to occurrences (MAHCO) in Air Traffic Management utilising a Bayesian hierarchical predictive coding approach to the brain, and the benefits for just culture. *Transportation Research Procedia*, *66*, 201-213.

Wendong, W., Hanhao, L., Menghan, X., Yang, C., Xiaoqing, Y., Xing, M., & Bing, Z. (2020). Design and verification of a human-robot interaction system for upper limb exoskeleton rehabilitation. *Medical Engineering & Physics*, *79*, 19-25.

Wu, K. J., Tseng, M. L., Ali, M. H., Xue, B., Chiu, A. S. F., Fujii, M., . . . Bin, Y. (2021). Opportunity or threat in balancing social, economic and environmental impacts: The appearance of the Polar Silk Road. *Environmental Impact Assessment Review*, *88*. https://doi.org/10.1016/j.eiar.2021.106570

Xie, X., Wu, Y., Palacios-Marqués, D., & Ribeiro-Navarrete, S. (2022). Business networks and organizational resilience capacity in the digital age during COVID-19: A perspective utilizing organizational information processing theory. *Technological Forecasting and Social Change*, *177*, 121548.

Yu, W., Jin, D., Cai, W., Zhao, F., & Zhang, X. (2022). Towards tacit knowledge mining within context: Visual cognitive graph model and eye movement image interpretation. *Computer Methods and Programs in Biomedicine*, *226*, 107107.

Yun, Y., Ma, D., & Yang, M. (2021). Human-computer interaction-based decision support system with applications in data Mining. *Future Generation Computer Systems*, *114*, 285-289.

Zarghami, S. A., & Zwikael, O. (2022). Measuring project resilience—Learning from the past to enhance decision making in the face of disruption. *Decision Support Systems*, *160*, 113831.

Zhu, X., & Li, Y. (2023). The use of data-driven insight in ambidextrous digital transformation: How do resource orchestration, organizational strategic decision-making, and organizational agility matter? *Technological Forecasting and Social Change*, *196*, 122851.