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**Integrating Artificial Intelligence into Management Information Systems to Enhance Public Sector Decision-Making Quality; Mediating role of Trust in AI and moderating Effect of Computer Self-Efficacy between AIMIS and Trust in AI**


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**Abstract**

The integration of Artificial Intelligence into Management Information Systems has become increasingly important for enhancing decision-making quality in the public sector, where efficiency, transparency, and accuracy are critical. The present study examined the role of AI Integration into Management Information Systems in enhancing public sector decision-making quality, with a specific focus on the mediating role of Trust in Artificial Intelligence and the moderating effect of Computer Self-Efficacy on the relationship between AI integration and trust in AI. Grounded in technology acceptance and socio-technical system perspectives, this study adopted a quantitative, cross-sectional research design. Data were collected from 200 public sector employees holding managerial, administrative, and IT-related positions across multiple departments. Standardized self-report instruments were used to measure AI integration into MIS, trust in AI, computer self-efficacy, and decision-making quality. Statistical analyses were conducted using SPSS, including descriptive statistics, independent sample t-tests, ANOVA, correlation analysis, and mediation and moderated-mediation testing using PROCESS macro.

The results indicated that AI integration into Management Information Systems positively influences public sector decision-making quality, demonstrating that AI-enabled systems support more informed, timely, and effective decisions. Although trust in automated systems showed a significant association with decision-making quality, mediation analysis revealed that the indirect effect of trust was not statistically significant. This indicates that trust in automated systems does not function as a mediator in the relationship between AI integration into Management Information Systems (AIMIS) and decision-making quality. However, the moderation analysis revealed that Computer Self-Efficacy did not significantly moderate the relationship between AI integration into MIS and trust in AI, indicating that confidence in computer usage alone may not be sufficient to strengthen trust in AI-driven systems. Additionally, independent sample t-test results showed no significant gender differences in trust or decision-making outcomes, highlighting the consistency of AI-related perceptions across male and female employees. The findings contribute to the growing body of literature on AI adoption in the public sector by integrating technological and psychological factors into a single explanatory framework. The study offers valuable implications for policymakers, system developers, and public administrators aiming to leverage AI-enabled MIS for improved governance and decision-making.

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# Chapter 1

# Introduction

## 1.1 Background of the Study

The rapid adoption of digital technologies into the organizational decision processes has transformed the information collection, processing, and application in institutions. One of such technologies is Artificial Intelligence (AI), which has become a breakthrough that can increase efficiency, accuracy of prediction, and governance based on data (Sun & Medaglia, 2019). Globally, there is a growing trend where both the government and nongovernmental organizations are integrating AI in their Management Information Systems (MIS) to enhance their analytical power, automate operations, and reinforce managerial decision-making processes. This movement can be seen as an extension of the widespread trends in the world towards intelligent information infrastructures based on the use of machine learning, natural language processing, and algorithmic decision models (Sun & Medaglia, 2019).

In the government, AI has gained special importance in MIS implementation. The demands on governments have also increased in the areas of transparency, responsiveness, and the accurate delivery of services, and these demands require strong information management. The traditional MIS models, despite being necessary in keeping the records, reporting, and administrative coordination, frequently fail to process high-volume, high-velocity, and high-variety data produced in the contemporary bureaucratic setting (Kankanhalli et al., 2019). In contrast, AI-powered MIS can handle intricate data trends, make predictive analytics, and evidence-based decision-making in areas like health, tax, social welfare, policing, and city governance (Wirtz et al., 2019). Consequently, the world is witnessing a shift in public organizations that are shifting to intelligent MIS architecture to improve the speed and quality of judgments made by managers through the old information systems.

The quality of decision-making has been identified as one of the main organizational performance determinants, which affects managerial effectiveness, performance, and responsibility. The quality of a decision is mostly assessed according to its accuracy, timeliness, information fullness, and the capacity to integrate insights that are related to the future (Nobre & Tobias, 2019). In the state sector, the quality of decisions is even more serious since the administrative ones influence the citizens, resource distribution, and policy execution directly. Good decision-making leads to better service delivery, good governance, and successful implementation of the national development agendas (Andrews & Walle, 2013). Nevertheless, typical administrative environments faced by public managers are complex, with unclear policy conditions, quick shifts in consumer demands, and excessive amounts of structured and unstructured data. These circumstances pose a great restriction to the conventional Management Information Systems (MIS), which usually store and retrieve information but have little forecasting, pattern recognition, or intelligent reasoning (Laudon & Laudon, 2020).

Artificial Intelligence (AI) has become, in this regard, an effective technological driver that has the potential to transform the decision-making process at government institutions paradigmatically. AI offers computational models, including machine learning, natural language processing, and intelligent analytics that are able to work with large volumes of data, learn based on past trends, and provide actionable information with the minimum human participation (Sun & Medaglia, 2019). Compared to traditional MIS, which involves the manual analysis of the data, AI-enhanced MIS is capable of sorting information, raising red flags, and simulating alternative scenarios on its own, hence providing policymakers with a better understanding of the situation and analytical purity (Sun & Medaglia, 2019).

Among the core benefits of AI integration in MIS, it is possible to distinguish the accuracy and trustworthiness of decisions. The conservative settings of traditional decision-making in government agencies are prone to human fallacies, heuristic prejudices, and subjectivity, which are capable of corrupting managerial judgment (Kahneman, 2011). AI mitigates these distortions by coming up with insights that are statistically correlated, mathematically modeled, and empirically based. As an illustration, predictive algorithms may use past administrative data to predict upcoming service demands, detect problematic areas, or raise warning signs regarding abnormal procurement or financial transactions (Meijer & Bolívar, 2016). The abilities enable managers to make evidence-based decisions based on their intuition instead of basing them on intuition, which improves the quality and objectivity of the administrative decision on the whole. Another advantage of AI is that it enhances prompt decision-making. Decisions in the sphere of the public sector are often characterized by the need to respond quickly, in detecting the threat to the population, to regulate the traffic, or to process an application to the social welfare. MIS traditionally has sluggish data consolidation processes that tend to slow administrative action (Kankanhalli et al., 2019). By comparison, MIS based on AI will be capable of processing real-time data streams and providing real-time suggestions. Indicatively, machine learning-based intelligent decision-support systems have been demonstrated to expedite coordination of emergency response and optimize operations that support public safety (Crawford & Calo, 2016). Quickened and automated information processing minimizes the administrative bottlenecks in turning around more nimble and responsive public organizations.

The other important aspect of AI integration is that it has the potential to make information relevant and contextual. Raw data is not enough, but the filtered, prioritized, and contextually significant information is required by decision-makers. AI systems are used to analyze complex data sets by applying classification, clustering, and pattern-recognition models to structured insights that meet a particular decision requirement (Wirtz et al., 2019). AI can be used to analyze sentiment to measure citizens' feedback, summarize policy documents through natural language processing, and check images through machine vision, or be used to verify or audit policy documents through sentiment analysis. The result of these enhanced knowledge outputs is a better decision-making process that is more informed and context-sensitive in the realms of the public sector. Moreover, AI allows decision-makers to simulate scenarios and forecast outcomes that are not available in the traditional MIS. Machine learning and neural networks provide a model to organizations to evaluate various policy alternatives, examine the expected outcomes, and estimate the risks before the implementation of decisions (Shrestha et al., 2019). These abilities are particularly applicable in complicated settings such as taxation, city planning, medical care, and security, where choices are long-term. Sharma et al. (2020) found that AI-based forecasting technologies can greatly enhance the planning process on the administrative side to define the future resource needs, forecast the behavioral patterns, and define potential disruptions. Consequently, decision-making is no longer reactive but proactive in the form of governance.

Besides enhancing analytical ability, the use of AI has the benefit of minimizing information overload, which is known to be a problem among government agencies. Managers are often faced with too much data and databases that are disjointed and located in various departments. The integration with the help of AI is achieved in terms of data mining, automated categorization, and intelligent retrieval mechanisms, which allow managers to retrieve only the most important information (Parycek et al., 2020). It facilitates decision-making and ensures less cognitive exhaustion in manual data screening.

The results of empirical research also show that AI-assisted decision-making environments achieve better results. According to the study by De Fauw et al. (2020), an AI-assisted decision model decreased diagnostic errors and increased the accuracy of judgment in the social health infrastructures. The same was found in the case of the public finance and regulatory agencies, where AI analytics accelerated better fraud detection and enhanced compliance tracking (Giest, 2017). These findings highlight the possibility of AI to take decision-making to a new level that is not possible with the current MIS discussion models. Nonetheless, the advantages of the AI implementation are conditional upon a number of organizational factors. Studies indicate that AI systems are best used when they are integrated into strong MIS systems that facilitate data standardization, inter-departmentalization, and orderly work processes (Luna-Reyes & Gil-Garcia, 2014). In the absence of adequate MIS bases, AI instruments can generate piecemeal information or false forecasts. Thus, the adoption of AI in MIS is not a technological enhancement but a paradigm shifts in the company, a process that improves the information circulation, analytical services, and management decision-making. Furthermore, the integration of AI transforms the role of public managers because the interpretation of data during their decision-making process is redirected to the human-machine interaction. This hybrid model spurs managers to integrate both knowledge of the domain and algorithmic intelligence. Research shows that judgments reached during this form of collaboration are more precise, uniform, and creative than those reached by people or algorithms (Rahwan et al., 2019). AI offers analytical rigor, human judgment offers contextual, appropriate, ethical, and socio-political sensitivity elements that are required in the governance of the public sector.

Even though AI has potential, organizations will not be able to benefit because of the presence of intelligent systems, and employees and decision-makers will not trust the data provided by algorithms. Mistrust in AI has thus become a key mediator that dictates the performance of AI-enabled systems. The employees might be reluctant to follow the recommendations provided by AI because of the fear of a lack of transparency, fairness, data privacy, and algorithm errors (Glikson & Woolley, 2020). In the government setting where the outcomes of decisions are highly social, it may be even more likely that people do not trust automated systems.

Trust in AI is described as the readiness of users to rely on AI systems when the circumstances are ambiguous (Siau & Wang, 2018). Studies indicate that trust grows when users believe that the AI systems are trustworthy, comprehensible, and that they adhere to the organizational ethical standards. Low trust, on the other hand, may render intelligent MIS less useful by lowering its rate of uptake, automation resistance, and unwillingness to use AI-generated insights in managing enterprises. Theoretically, trust is the mechanism through which the incorporation of AI is connected to the quality of decisions, which identifies whether employees apply intelligent technologies efficiently (Longoni & Cian, 2022). Thus, the mediating effect of trust is critical to assessing the effects of AI-based MIS on the results of making decisions in governmental organizations.

Personal technological ability also determines the willingness of employees to communicate with smart systems. The moderating factor that is important in influencing how users will interact with AI that is incorporated in MIS is computer self-efficacy (CSE), which consists of the belief in the ability to utilize digital technology (Compeau & Higgins, 1995). High CSE employees have a higher likelihood of investigating AI features, understanding analytics, resolving system problems, and implementing AI insight in decision-making. Conversely, people with low CSE might get scared of complicated systems and avoid them, commit mistakes, or use AI features to a lesser extent.

The studies have shown that CSE is also associated with technology adoption and intensity of user interaction and perceived usefulness of information systems (Venkatesh et al., 2012). High CSE enhances the connection between AI introduction and trust in AI-enabled settings, as users who are confident in AI results are more positive in judging AI outputs and ready to use automated analytics (Ghazizadeh et al., 2012). CSE then mediates the connection between AI integration and building trust, and its usefulness in enhancing the quality of decision-making by AI tools. Given the different technological abilities of employees in the Pakistani public sector, it is important to study this moderating position.

Digital transformation has already made digital transformation into a national focus in Pakistan, and has been reflected through the Digital Pakistan initiative, e-governance initiatives, and provincial smart initiatives. Islamabad and Rawalpindi have been experiencing an increase in the adoption of MIS in administrative functions, reporting, and internal coordination by the public organizations within the areas, such as ministries, regulatory bodies, municipal administration, and the departments attached to them (Bari et al., 2022). Nevertheless, most MIS infrastructures are underdeveloped and do not have superior analytic functions. Consequently, decision-making is usually based on experience, manual reporting, or fragmented sources of information instead of using real-time data analytics. Recent reports show that the use of AI in governance has become more attractive, especially in tax surveillance, law enforcement, medical imaging, transportation, and automation in administration (Hussain et al., 2023). However, institutional obstacles, i.e., low level of technical capability, financial resources, institutional opposition, and absence of standard AI policies, delay the usage of AI-based MIS in government institutions. Employee willingness to rely on AI systems is also a crucial issue that defines the success or failure of adoption, particularly where the data involved is sensitive to people.

Moreover, the Pakistani public sector has special problems, such as bureaucratic issues, a lack of interoperability between information systems, and a lack of trained data analysts. AI can be used to resolve these problems through assisting transparent decisions, reducing human mistakes, identifying anomalies, and enhancing administrative effectiveness (Khan & Qureshi, 2021). Nevertheless, the success of AI integration directly depends on the perception and ability of the user, which confirms the relevance of studying the concept of trust and computer self-efficacy in local public institutions.

### 1.2 Industry Context

The government of Pakistan is gradually yet significantly transforming its attitude to governance, the provision of public services, and administrative effectiveness, and it is this changing climate that creates the setting in which the adoption of artificial intelligence (AI) into the current management information systems (MIS) can be considered. AI is also viewed as the instrument to bring the Pakistani government systems into the modern era by streamlining the processes of providing services and optimizing the results of the policies developed by the governmental bodies in the country (Kankanhalli et al., 2019). Scholars suggest that AI-based solutions have the potential of increased transparency, speed, and effectiveness in all public-sector capabilities, including social welfare and citizen services, as well as administrative planning (Zahra & Shah, 2025).

However, despite this identified potential, the application of AI is still scarce within the context of the public organization. One of them is structural and institutional barriers, most government agencies continue to use old MIS systems that facilitate only low-level data storage and record-keeping and do not provide sophisticated analytics or decision support (Nazeer & Gil, 2023). This means that workflows in such systems are siloed and little data is shared between departments, and procedural delays are the norm, limiting the potential of intelligent automation or predictive analytics. This is further increased by the fact that not all public institutions are ICT-ready, particularly at the lower levels, which reduces the feasibility of implementing AI tools that consume a lot of resources (Nazeer & Gil, 2023). In addition, governmental institutions are characterized by a high level of budget limitations and official procurement practices. The investment cycles of funding frequently favor operational continuity over technology development and thus can be very challenging to make a case in large-scale investments into AI, specialized hardware, or maintenance, when the payback is not immediately apparent (Nazeer & Gil, 2023; Hussain, Rizwan, 2024). Sluggish approval, absence of dedicated AI funds, and indecisiveness of the decision-makers further suppress further development.

The other critical factor is human capital. Numerous state organizations lack access to personnel with knowledge of AI and data analytics or advanced IT management. Such scarcity results in reluctance to embrace AI-driven MIS despite the fact that the institution envisions the modernization, as the administrators have not been convinced that the staff are technically literate or have the confidence to operate, interpret, and manage AI-based applications (Ali et al., 2025). In the absence of staff who can find their way around AI tools, they can be abused, used poorly, or fail to work. The ethical and regulatory setting is also cumbersome. Although growing discussions on digital governance are being heard in Pakistan, formal laws or legislations on data privacy, algorithmic transparency, and ethical AI applications are still in their infancy. Researchers warn that the implementation of AI without considering the issue of data governance and privacy may cause mistrust in the population and opposition among the citizens and bureaucrats (Jadoon et al., 2025). Without good laws and ethics on data protection, institutions might not readily integrate AI in decision-making, particularly when personal or administrative data that is sensitive is to be used.

In spite of these challenges, positive indicators of the willingness and increasing institutional interest in AI-enabled governance are present. The recent suggestions and studies emphasize how the incorporation of AI, particularly in the form of pilot projects and locally-based initiatives, can help to significantly enhance the transparency, shorten processing times, and improve the policy-making process and service delivery (Zahra & Shah, 2025). As an illustration, the utilization of data analytics and AI-based policy-support programs can assist state organizations with regard to anticipating demands, distributing resources in a better manner, and simplifying the interaction with citizens. This is an expression of recent initiatives to rethink bureaucratic efficiency by using so-called smart governance, substituting the former paper-based and manual operations with digital and data-driven ones (Ahmad & Elahi, 2025).

Moreover, the social consciousness and demands are changing. There is a growing exposure of the citizens to digital public services (e.g., e-filing, online applications, automated tax or service portals), which in its turn leads to the increasing demand for digital governance response, transparency, and accountability (Shah et al., 2025). This transformation puts the strain on the public organizations to upgrade their information systems not only to ensure data management but to have intelligent analytics, decision support, and proactive governance. These pressures, combined with institutional acknowledgement of the usefulness of AI means that AI-MIS integration is not only welcome, but it is vital to the provision of on governance promises.

Thus, the context around the industry presents a transitional juncture of a public sector: one where conventional information systems and bureaucratic frameworks no longer suffice to address the needs of modern administration, but the institutional vision, pressure of needs, and the accelerated technological consciousness offer desirable opportunities to transform AI-based technology. The combination of infrastructural, human-capacity, regulatory, and shifting societal demands creates the possibility of AI integration, which is both an opportunity and a challenge. In this respect, the study of the impact of AI integration into the MIS on the quality of decision-making, under which human and institutional conditions are to be under consideration, can be defined as extremely topical and timely.

### 1.3 Research Problem

Although the utilization of artificial intelligence (AI) in the management of the public administration has become more widespread in many countries worldwide, people have little empirical insight in how the integration of AI in the management information system (MIS) would affect the quality of decisions made within the public-sector organizations, especially in developing countries such as Pakistan (Madan & Ashok, 2023). Public authorities in Islamabad and Rawalpindi still have a high level of reliance on traditional MIS, which do not require high-quality data analysis and forecasting, leading to inaccurate and unsupported administrative decisions (Aarab et al., 2025). Furthermore, the successful use of AI is not only technologically preconditioned but also human: trust in AI and self-efficacy in using computers play a significant role in whether the generated insights will be successfully applied to making decisions (Alon-Barkat & Busuioc, 2022). Empirical research on these behavioral and organizational mechanisms is relatively uncommon in Pakistan, and most studies are dedicated to the opportunity and challenge of concepts instead of solid and context-focused evidence (Rana et al., 2024). As a result, the nature of AI integration with trust and user competence without such knowledge can lead to failure of the AI initiatives in the public-sector to positively impact the quality of decisions and produce the desired governance implications. The proposed research aims to fill this gap with an empirical investigation of the impact of AI integration in MIS on the quality of decisions made in public organizations of Islamabad and Rawalpindi, as well as considering the role of trust in AI and the moderating effect of computer self-efficacy.

### 1.4 Problem Statement

In Islamabad and Rawalpindi, the organizational structure of the public sector cannot make efficient and accurate decisions because of the restrictions in the traditional MIS. Even though AI can be used to improve decision-making, its use is not widespread, and its success is predetermined by human factors, including trust in AI and computer self-efficacy. Empirical studies of the effects of AI integration on the quality of decision-making and the importance of these human factors are deficient, which necessitates a systematized investigation of the subject on the local level of the state-backed sector.

### 1.5 Research Gap

Even though the topic of introducing artificial intelligence (AI) to the sphere of the public administration has gained growing interest over the last several years, there still are critical gaps in the empirical literature related to the aspects of AI integration into the Management Information Systems (MIS) translating to the quality of decisions in the context of the public sector and to the conditions of its introduction under the banner of human and organizational factors.

To begin with, much of the current literature on AI in the government sector focuses on general adoption patterns, overall efficiency, or capacity to deliver services, but not the quality of decisions. The majority of studies focus on the application of concepts or services aimed at the citizens, without carefully evaluating whether AI provides more correct, timely, or strong decisions in government operations (Matias-Pereira, 2025; Bokhari et al., 2025). It means that there is a conceptual gap because there is not enough empirical data to support the interrelation between the use of AI-empowered MIS and enhanced decision outputs in policy planning, resource allocation, and administrative decisions.

Second, existing studies rarely adopt the holistic, multi-level model that concurrently takes into consideration the factors of institutional readiness, system integration, and human behavior. Systematic reviews reveal such barriers as fragmented data systems, poor digital infrastructure, incompetencies of the staff, and the absence of governance frameworks, but there is a paucity of empirical studies modeling the interplay between these conditions to influence the outcomes of AI adoption in governance settings (Mikalef et al., 2024; Selten & Klievink, 2024). In the absence of a comprehensive strategy, it is not clear under what circumstances and under what combinations of institutional, technical, and human factors AI integration improves decision-making, and it may not work in certain situations.

Third, there is a lack of research investigating mediating or moderating psychological and behavioral variables, including trust in AI systems or computer self-efficacy. Numerous studies have concentrated on technical or governance issues and do not cover the role of perceptions of users, confidence, or willingness to trust AI in real utilization and results. As an example, Batool, Zowghi & Bano, (2025) present general issues such as ethics, governance, and capacity-building but fail to examine the question of whether trust or user competence dictates the successful adoption of AI in the context of decision-making.

Fourth, most empirical studies on AI in government are based in developed nations or where there is strong digital infrastructure, which has a geographic and contextual imbalance in developing nations such as Pakistan. The institutional factors, budget constraints, the presence of old MIS systems, and bureaucratic organization in Pakistan are not similar to those of developed nations, and there is very little empirical evidence to study how the integration of AI is implemented within such contexts (Selten & Klievink, 2024).

Fifth, although the AI integration has been researched in relation to the results of decision-making or governance, it is usually related to the efficiency of service delivery, the automation of administration, or internal operations, and not to the quality of the outcomes of strategic decision-making, policy formulation, or governance. Available literature demonstrates that the use of AI can assist with more mundane administrative functions, but the role of this tool in making high-stakes decisions in governmental organizations is under-researched (Haesevoets et al., 2025; Mikalef et al., 2024).

Lastly, although literature focuses on the necessity of data quality and infrastructure consistency as well as workforce skills, process redesign, and governance reform to responsibly adopt AI in the public administration, there is a lack of empirical studies that test frameworks that integrate the concept of data quality with infrastructure and workforce skills with process redesign along with governance reform (Bokhari et al., 2025). This restricts the knowledge about the routes through which the incorporation of AI in MIS is transformed into better decision-making performance and the circumstances in which it works.

With these gaps, the absence of empirical evidence on the relationship between AI-MIS integration and quality of decision-making, the insufficiently researched behavioral moderators and mediators, and the dearth of context-specific research in developing nations, there is a definite opportunity to conduct systematic research on the impacts of AI integration on decision-making in organizations of the public sector and the influence of such human factors as trust in AI and computer self-efficacy on the quality of the latter. The proposed research on the subject of public organizations in Islamabad and Rawalpindi will fill this gap through a mediated-moderation model in a developing country setting.

### 1.6 Research Objectives

1. To investigate the direct impact of the integration of AI into MIS on the quality of decision-making.
2. To determine whether trust in automated systems is an intervening or mediating variable between AI integration into MIS and quality of decision-making.
3. To examine the existence of a relationship between AI integration into MIS and Trust in AI, with the moderating effect of computer self-efficacy, in such a way that the association between the two grows stronger as technology self-efficacy increases.
4. To examine whether decision-making quality (DMQ) differs across employees' demographic characteristics, including gender, education level, department, and years of professional experience.

### 1.7 Research Questions

1. Does AI integration into MIS directly improve decision-making quality in public-sector organizations?

2. Does trust in automated systems mediate the relationship between AI integration into MIS and decision-making quality?
3. Does computer self-efficacy moderate the relationship between AI integration into MIS and Trust in AI?
4. Does decision-making quality (DMQ) differ significantly based on employees' gender, education level, department, or years of experience?

### 1.8 Hypotheses

H1: The AI integration into MIS positively and significantly correlated with the quality of decision-making.

H2: Trust in automated systems mediates the relationship between AI integration in MIS and the quality of decisions made.

H3: The relationship between AI integration into MIS and Trust in AI is moderated by computer self-efficacy.

H4: There is a significant difference in decision-making quality (DMQ) among employees based on their gender, education level, department, and years of professional experience**.**

### 1.9 Research Significance

This study is important in its potential contribution not only to the theoretical but also practical insights on the application of artificial intelligence (AI) in the management of the government sector. Theoretically, the proposed study contributes to the area of research in the field of public administration and information systems because it empirically investigates the association between the implementation of AI in the Management Information System (MIS) and decision quality. Although the former research has been driven mainly by technical feasibility or operational performance, the proposed study closes an important gap by examining the quality of the decision-making process as an important outcome measure, thus offering a more refined picture of the effect of AI on organizational performance.

Human and behavioral factors are also taken into consideration in the study, and this ultimately contributes to the theory as well. In particular, it investigates the mediating effect of trust in AI and the moderating effect of computer self-efficacy, thereby broadening the existing knowledge of technology-adoption and acceptance in the organizational context. Examining the effects of trust and self-efficacy on the effectiveness of AI-enabled MIS, the study can contribute to a better understanding of the mechanisms by which AI technologies could be effectively deployed in multifaceted and hierarchical contexts of the public sector.

Practically speaking, the results of this study can be of much use to policymakers, administrators, as well as managers in the sector serving the people in Pakistan and other developing nations. The major problems that have been witnessed with public organizations are ineffective decision-making, bureaucratic delays, and a lack of effective utilization of technology. This study can inform the development of AI-enabled systems in more efficient ways by public institutions by identifying the circumstances in which AI integration could enhance the quality of decision-making. An understanding of the functions of trust and computer self-efficacy can be implemented in training programs, change management, and capacity-building programs, so that employees are willing and capable of applying AI tools effectively.

Moreover, the research is part of the bigger objective of evidence-based governance. Positive policy development, service delivery, and administrative transparency, because of the better decisions made with the help of AI show can benefit the citizens and other stakeholders. The research also offers context-specific findings by targeting the public-sector organizations in the city of Islamabad and Rawalpindi, which can help in the realization of the context-specific infrastructural, cultural, and organizational issues of developing-country environments, which are usually ignored in research carried out in developed countries.

Lastly, this study provides strategic direction on how future research in the digital transformation of the public sector can be implemented. The knowledge of the interaction of AI technology, human factors, and organizational outcomes will provide leaders with practical information to capitalize on the advantages of AI integration. The empirical results may be used as the basis of future studies in the area of AI adoption, digital governance, and innovation in the sphere of the public sector that will promote more credible and knowledge-based decision-making.

### 1.10 Operational Definitions

Theoretical and empirical studies provide material that is used to define the key concepts used in the study.

### 1.10.1 AI Integration into MIS

The degree of artificial intelligence tool and algorithm integration into Management Information Systems (MIS) is known as AI integration in management information systems that is used to help make decisions based on data, develop greater data analytics, and improve administration is known as AI integration into Management Information Systems (MIS). The AI Integration into MIS Scale (AIMIS-10) is the operationalization of this construct and comprises ten items that measure the existence of AI-based analytics, predictive models, automated insights, and AI-driven workflows in MIS (Bokhari et al., 2025). The respondents answered in accordance with each statement on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The scores are higher, which means more AI technologies are integrated into MIS, which are high digital capabilities of the public-sector decision-support systems.

### 1.10.2 Decision-Making Quality

The quality of decisions made by the managers of the public sector based on the MIS and AI-supported results is defined as decision-making quality (Bokhari et al., 2025). The scale used to measure this variable is the Decision-Making Quality Scale (DMQS-10), comprising 10 questions that gauge the extent to which they make meaningful decisions and at the right time, meeting their goals, and having their decisions accepted by stakeholders (Bokhari et al., 2025). The answers are noted on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The higher the scores, the better the quality of decisions that are made with the help of AI-integrated MIS, as it demonstrates that the decisions are of high quality, the problem is solved better, and the stakeholders are taken into account.

### 1.10.3 Trust in Automated Systems

Trust in automated systems refers to the extent of confidence and dependence between employees of the public sector on AI systems and automated decision support tools (Jian, Bisantz, & Drury, 2000). The measure of this construct is based on the Trust in Automated Systems (TIAS) scale, which was created by Jian, Bisantz, and Drury (2000), and which consists of twelve items to reflect both trust (positive) and distrust (negative) perceptions of AI systems. The ratings of the participants concerning their agreement are rated on a 7-point scale (1 = Not at all to 7 = Extremely), and the negative items are reverse-coded before the computation of the overall trust score. The high scores show increased trust in the integrity, reliability, and dependability of the AI system and that users are more eager to use automated results to make an informed decision (Jian, Bisantz & Drury, 2000; Lee & See, 2004).

### 1.10.4 Computer Self-Efficacy

Computer self-efficacy refers to the conviction that a person can effectively accomplish things with the help of computer technologies (Compeau & Higgins, 1995; Marakas et al., 1998). The Brief Inventory of Technology Self-Efficacy Short Form (BITS-SF) that involves six items in dichotomous format (Yes/No) to assess the confidence of the users in performing specific computer-related tasks is used to operationalize this variable, which includes items like using task manager, browsing the Internet, programming, or configuring hardware (Compeau & Higgins, 1995; Marakas et., 1998). The number of Yes answers equals 1, and the number of No answers equals 0 having total score of 0-6. An increase in total scores suggests that there is an increase in computer self-efficacy, which reflects an increase in competence and confidence in dealing with technology. The construct is taken as a moderator of the research, and it has a role in the strength of the association between the introduction of AI in MIS and trust in AI.

## 1.11 Chapter Summary

The chapter serves as a thorough foundation for the current study, as it puts the research problem into perspective, outlines gaps in the existing literature, and provides the theoretical and practical implications of integrating AI into Management Information Systems (MIS) in the Government sector. The chapter commenced with a background of the use of AI in improving the quality of decision-making, where AI-enabled MIS can enhance the quality of the decisions made by managers in the public sector in the aspects of accuracy, timeliness, and relevancy. It highlighted how AI technologies (e.g., predictive analytics, machine learning) can be leveraged to transform traditional administrative processes into more advanced, data-driven governance processes, which in turn can help organizations become more efficient and effective. The industry environment was also described in detail to portray the importance of the research in the definite context of Pakistan, with special reference to the organization of the public sector in the city of Islamabad and Rawalpindi.

The problem statement and research problem were then framed, so that it is determined that the adoption of AI by the government administration has become popular, yet the impact that it has on the quality of decisions is under-researched. The issue statement identified the fact that although AI-enabled MIS can potentially positively influence decision-making, the challenge encountered in the public sector organizations is often the inability to integrate the technology, the lack of human competence, the lack of trust in AI systems, and institutional readiness. These issues warrant the necessity of the research that will investigate the connections between AI integration, trust in AI, computer self-efficacy, and quality of decision-making.

The analysis of the research gaps showed that the current research is usually concerned with general AI adoption, service delivery, or operational efficiency, but little is mentioned with respect to high-stakes decision-making outcomes. In addition, past studies have not given much attention to the contributions of human and behavioral variables, including trust in AI and computer self-efficacy, towards the effectiveness of AI implementation in MIS. After defining the research gaps, the chapter provided the research objectives, questions, and hypotheses, which are used to direct the empirical investigation as a whole. The research hypothesis is to explore how the use of AI in MIS has a direct impact on the quality of decisions, the mediating role of trust in AI, and the moderating impact of computer self-efficacy between AI integration and trust in AI. These questions and assumptions will give a formal basis for testing the proposed relationships and filling the gaps that have been identified in the literature.

Lastly, the chapter operationalized the key variables on validated scales. The theoretical constructs in each of the operational definitions are explicitly related to quantifiable indicators to ensure the methodological rigor of the study and allow gathering and analyzing data reliably. The chapter forms a strong theoretical and practical foundation of the study, with its significance of AI incorporation in the MIS of the public sector, gaps in the literature, and a systematized research design. This study can contribute to theory and practice by providing an understanding of how artificial intelligence can be used to improve the quality of decision-making processes in the public-sector organizations, especially in the framework of developing nations, such as Pakistan.

# Chapter 2

## Literature Review

### 2.1 Integration of AI into MIS and Decision-Making Quality

The integration of Artificial Intelligence (AI) in Management Information Systems (MIS) has been gaining acceptance as one of the ways of improving the quality of decision-making within an organization. A number of recent empirical studies confirm the idea that MIS with AI can result in better accuracy and timeliness in decision-making, better strategic acumen, and better operational efficiency. During a cross-sector empirical research focusing on companies that implemented AI, Górka, Baran, and others (2025) discovered that after introducing AI, the companies claimed to have seen significant changes in how they make managerial decisions: they became quicker, more transparent, and evidence-based. Their survey of several industries revealed that AI systems are useful in speeding up the data analysis process, decreasing the number of human errors, and offering organized and reliable results - all of which add to the improvement of the performance of decisions (Górka et al., 2025). This implies that the implementation of AI changes the avenues of decision-making to be not based on subjectivity or intuition but rather be supported by data and be analytic in nature. Organizations have reported strategic decision support gains in environments where MIS is augmented by AI features, like predictive analytics, pattern detection, automated data processing, and so on. As an example, an empirical study on business organizations based on AI-powered MIS found that the abilities of predictive analytics, an effective data processing framework, automated routine tasks, and risk management were used together to positively affect the quality of managerial decisions (Gangwar et al., 2024). Timely insights into large data were available in AI MIS in their sample, allowing the managers to predict and exclude risks as well as make proactive decisions instead of reactive ones.

In addition to the individual sector of the economy, the integration of AI in decision support systems is also promising in the field of the state and its administration. A methodological survey of AI integration in e-government agencies around the globe revealed that AI-based applications, such as data-based decision-making solutions, predictive analytics, and automation, have a positive impact on better government performance, effective service operation, and decision responsiveness (Alshaer, 2024). According to the review, there is one commonality: in case the AI is integrated into MIS and is supported by the institutional preparedness, the quality of decisions is likely to improve, though it depends on the data governance, infrastructure, and organizational adjustment (Gangwar et al., 2024).

The role of AI in decision support is not just about efficiency but also about more complicated, uncertain, or dynamic decisions. In any area where the variables to be considered in decision-making are numerous, or the future outcomes are uncertain, or the results need to be predicted (such as in strategic planning or resource allocation), the analytical properties of AI-enhanced MIS (or decision support systems) are beyond human ability (Abdelmouttalib & Tabaa, 2025). Their study of the AI-based decision support systems revealed that AI can improve situation planning, risk, and resource optimization, and consequently, it can assist in making sound strategic decision-making that otherwise would be challenging or time-consuming when it was done by humans.

At a more basic level, the review of AI-MIS integration in all its subjects highlights the dual advantage of the power of data-processing and predictive analytics in enhancing both operations and strategic decision-making. The study by Alifan, Al Qawasmeh, Liban, Mohamed, and El Ebiary (2025) provides a systematic literature review of the literature on AI implementation into MIS, and the authors concluded that in different sectors, organizations have witnessed the following benefits after integration of AI-enhanced MIS: an increase in reliability of decision-making, a decrease in workload, and analytical depth. They emphasize that AI allows MIS to transform passive data storage into active decision-making machines that assist not only with routine but also with complex management tasks (Alifan et al., 2025).

However, according to some researchers, the positive outcomes of AI MIS integration do not necessarily result in a good decision. A recent survey of AI-based decision-making in the environments of the public sector suggested that, although AI can provide strong predictive analytics and data-processing capabilities, the quality of decisions heavily relies on the correspondence of the results of artificial intelligence to the organizational context, policy goals, and human judgment (Fischer et al., 2023). Their critique highlights that machine-learning systems can easily assume that data can be at rest and that they fail to work in dynamically changing settings typical of the public administration sector, which can undermine the validity of the decisions in case the AI results are accepted literally without human intervention (Fischer et al., 2023).

In addition, Ghasemaghaei (2020) discovered in a longitudinal study of the use of data analytics and decision quality in organizations that data analytics is only beneficial in enhancing decision quality when it is supported by robust knowledge-sharing strategies and organizational competencies. Even though this paper has not specifically studied AI, it highlights the fact that even highly developed information systems, such as AI elements, will only improve the quality of any decision that the company makes once organizational culture, data management, and human capabilities allow making the best use of them (Ghasemaghaei, 2020).

Overall, the literature offers an overall positive correlation between AI integration in MIS and the quality of decisions. MIS with AI can enhance speed, accuracy, and strategic depth of decision-making processes by automating decisions, predicting analytics, aiding in risk analysis, and releasing decision-makers from straightforward tasks. But this is not the only bright side; the achievement of the quality of decisions is a situational factor, with organizational preparedness, information governance, compatibility with decision situations, and human control being factors. This indicates the necessity to conduct empirical research that will consider not only whether AI-MIS integration exists but also when and under which circumstances it can contribute to better decision-making, which is exactly what this study aims to fill the gap.

The literature on AI adoption and human-computer interaction is becoming more and more clear that technical adoption of AI is just a part of the job; the question of whether AI systems have any effect (such as the quality of decisions) is heavily rooted in human factors, the primary among them being, trust in the AI system, and self-efficacy of the users towards technology.

### 2.2 Trust in AI / Automated Systems

Trust in AI (or automated systems) is the level of confidence that users have in the reliability, integrity, transparency, and dependability of automated systems. A meta-analysis study on user trust in AI-enabled systems points to the fact that three overall categories of variables influence user trust: socio-ethical, technical/design features, and user characteristics (Bach et al., 2023). The review states that the development of trust is not limited to the implementation of powerful algorithms, but also entails transparency in design, engagement with users, evident communication of system constraints, as well as continuous human-centered control (Bach et al., 2023). Unless these dimensions are dealt with, technical sophistication may not prompt adoption or dependency. The idea is supported by empirical evidence. Trust was reported to be a significant factor in acceptance of AI technologies, and the authors identified two dimensions of trust, namely, functionality trust (confidence in system performance) and human-like trust (perceived social or anthropomorphic features), with the effect of functionality trust being significantly stronger in the adoption of AI (Choung et al., 2022). This implies that in organizational cultures like public-sector MIS, users would depend mostly on the results of AI when they have confidence that the system is reliable and would give them the correct results.

In relation to contexts involving the use of AI in the realm of public governance, studies that investigate the role and utilization of AI in service automation and decision-support systems concluded that the automation of services and decision support systems by AI have a positive impact on stakeholder trust and engagement, which subsequently contribute to the creation of organizational change and better governance results (Andrews et., 2022). This confirms that trust might be a mediator: the AI integration might have better results only in case its users or stakeholders have enough trust in the AI-based system to adopt and use the outputs of the system.

Trust is extremely important in high-stakes sectors like healthcare. The systematic review of trust in AI-based clinical decision support systems (AI-CDSS) among healthcare workers found that transparency, usability, training and familiarity, system reliability, and ethical/design considerations were important factors that determined trust (Tun et al., 2025). AI systems that were not built or trained with user involvement were perceived as unreliable or unclear, which was why they were not adopted/used with caution. To ensure that AI has a positive effect on the quality of decisions, it is crucial to build trust.

Lastly, research on human-computer trust is theoretical, stating that to achieve trustworthy AI, the design must be human-centered, constantly validated, explainable, and have accountability mechanisms. The absence of them makes it more likely that the AI systems will assist decision-making effectively with the risks of over-trust (blind reliance) and under-trust (suspicion, rejection). Combined, these findings reflect that trust is not a unilateral or accidental phenomenon; it is a core facilitator between integrating AI and actual system utilization and functionality. In the case of the public-sector MIS, where the decisions influence the citizens, the policy, and the public resources, trust is particularly critical, as the decision should be transparent, justifiable, accountable, and consistent with the values of the people.

### 2.3 Computer Self Efficacy

Computer self-efficacy refers to the personal belief about the ability of an individual to effectively interact with computer technologies in terms of learning, using, understanding outputs, and incorporating the results into decision-making (Compeau & Higgins, 1995; Marakas et al., 1998). Within the framework of AI-enabled systems, CSE emerges as a significant factor that can either precondition the feeling of competence in people to communicate, evaluate, and trust AI outputs.

Empirical studies that have been quite recent provide evidence of a close relationship between technology self-efficacy and automated systems trust. An organizational sample study indicated that organizational participants with greater technology self-efficacy indicated a stronger desire to trust automated technology, which positively aligned with AI acceptance, and negatively with fear of AI (Husemann et al., 2023). It implies that the self-perception of users in terms of their technological abilities can affect their readiness to trust AI, minimize the fear factor, and encourage the use of AI.

Similarly, in the field of education and organizations, researchers have found that the computer self-efficacy of people is an indicator of their intentions to use ICT tools; highly self-efficacious people tend to use technology and embrace innovative digital applications (Ferdousi, 2019). Though these are not studies focused on AI in particular, but on the general ICT, the same principle applies: self-efficacy determines the willingness of the users to work with technology. Furthermore, elaborations of classical technology adoption models emphasize the idea that affective and cognitive determinants, such as self-efficacy and trust, in the AI adoption setting, have an impact on the usage behavior in addition to performance and effort expectancy (Wolfe et al., 2025). This implies that CSE may moderate the translation to trust, adoption, and effective use of AI integration in an organizational setting.

In other investigations of ICT use, technology self-efficacy not only has an impact on the behavioral intentions of users but also moderates the effects of educational and motivational factors on actual technology use, which is often through increased motivation, engagement, and cognitive preparedness (Marasinghe et al., 2024; Xie et al., 2022; Huang & Liaw, 2018). Applying this reasoning to MIS in the public sector implies that administrators whose self-efficacy in using computers is higher can be more willing to explore, interpret, and believe AI-added decision-support outputs and use AI integration as a better source of decision-making.

Thus, computer self-efficacy may be theorized as a moderating variable that may influence the quality of the relationship between AI integration (technical capability) and trust in AI (psychological acceptance). In the case of high self-efficacy, users might be at ease and confident in using AI MIS; in the case of low self-efficacy, even well-integrated AI systems might not be used or trusted.

### 2.4 Theoretical Foundations

The Social Cognitive Theory (SCT) proposed by Bandura (1986) provides a comprehensive framework for understanding how individuals interact with their environment and how cognitive processes influence behavior and outcomes. Within organizational settings, SCT emphasizes that behavior is shaped through the reciprocal interaction of environmental factors, personal beliefs, and cognitive appraisals. When applied to AI integration into Management Information Systems (MIS), SCT helps explain how technological environments, individual cognition, and personal capabilities jointly influence the quality of decision-making. Decision-making is not merely a function of system availability but is shaped by how individuals cognitively interpret and psychologically engage with AI-supported environments.

From the perspective of SCT, AI integration into MIS represents an important environmental determinant. The incorporation of AI-driven analytics, predictive algorithms, and automated decision-support tools enhances the informational environment by offering timely, data-driven insights that can improve decision accuracy and efficiency. Such technologically enriched environments are expected to facilitate higher-quality decisions by reducing uncertainty and cognitive load (Wolfe et al., 2025). However, SCT posits that environmental inputs alone do not directly determine behavior. Instead, individuals must cognitively process, evaluate, and accept these environmental cues before they can influence decision-related behaviors. Thus, the mere integration of AI into MIS does not automatically lead to improved decision-making quality; its impact depends on users' cognitive responses to the system.

Trust in AI functions as a critical cognitive appraisal mechanism within SCT. Trust reflects users' beliefs regarding the reliability, transparency, and accuracy of AI systems. According to SCT, behavioral outcomes are guided by such cognitive evaluations, as individuals are more likely to rely on systems they perceive as credible and dependable. When employees trust AI-integrated MIS, they are more inclined to incorporate AI-generated insights into their judgment processes, leading to more informed and evidence-based decisions. Conversely, low levels of trust may result in resistance or underutilization of AI recommendations, regardless of system sophistication. Therefore, trust in AI operates as a mediating variable that explains how AI integration into MIS translates into enhanced decision-making quality through increased reliance on AI-based information (Andrews et al., 2022).

Another key construct within SCT is self-efficacy, which refers to an individual's belief in their capability to successfully perform tasks and manage challenges. In the context of AI-powered MIS, computer or technology self-efficacy reflects users' confidence in their ability to understand, operate, and apply AI tools effectively. SCT suggests that individuals with higher self-efficacy are more proactive, resilient, and adaptive when interacting with complex technologies. Such individuals are better equipped to interpret AI outputs, critically evaluate recommendations, and integrate AI insights into decision-making processes. Consequently, high computer self-efficacy strengthens the development of trust in AI systems, as users feel competent and in control when engaging with the technology. In contrast, individuals with low self-efficacy may experience anxiety or confusion, which can weaken trust in AI even when advanced systems are present, thereby limiting the benefits of AI integration (Marasinghe et al., 2024).

SCT further emphasizes the principle of reciprocal determinism, wherein environmental systems, personal beliefs, and cognitive appraisals continuously interact to shape behavioral outcomes. In the present framework, AI-integrated MIS constitutes the environmental factor, trust in AI represents the cognitive appraisal, and computer self-efficacy functions as a personal belief that moderates this relationship. Together, these factors dynamically influence decision-making quality. Trust enables users to rely on AI insights, while self-efficacy determines the extent to which individuals can effectively engage with and benefit from AI systems. This interaction leads to more accurate, consistent, and evidence-based decision-making within organizations.

Overall, the Social Cognitive Theory provides a robust theoretical foundation for understanding the effects of AI integration into MIS on decision-making quality. The theory clarifies that AI enhances decision outcomes only when users cognitively trust the system and believe in their own ability to interact with it effectively. Trust in AI serves as a mediating mechanism through which environmental technological advancements influence decision quality, while computer self-efficacy moderates the strength of this pathway. Consequently, SCT offers a comprehensive and integrative explanation that logically connects all variables within the present research framework.

**Hypothesis 1: The AI integration into MIS positively and significantly correlated with the quality of decision-making.**

The factor of the key relationship between the integration of AI in MIS and the quality of the decision-making process has become an increasing focus of empirical research. The AI-based MIS improves the accuracy of the decisions, the speed of the information retrieval, and assists with making analytical arguments with the help of the machine learning models. Research demonstrated that systems that operate on AI minimize human judgmental mistakes and increase the precision of a decision by delivering real-time and data-driven insights (Davenport & Ronanki, 2018). In the organizational setting, the AI-based MIS solutions like predictive analytics, automated reporting, and intelligent dashboards would allow making more objective and reliable decisions, reducing the use of intuition only (Ransbotham et al., 2021).

The latest studies also indicate that MIS with AI can significantly enhance the quality of the decision made since it allows recognizing patterns, forecasting, and modeling complicated data that are beyond human ability (Jarrahi, 2018). These systems enable the employees to process large masses of information, thus resulting in better informed and more logic-based choices. As organizations are becoming more and more strategic and operational, decision accuracy, speed, and consistency have risen dramatically according to empirical evidence (Shrestha et al., 2019).

Moreover, MIS with AI can be used to make quality decisions, as the information transparency and uncertainty levels can be minimized, and employees can more thoroughly analyze alternatives (Ekpanyapong & Chamchong, 2021). AI integration in MIS can also facilitate multi-criteria decision making, with the help of which employees are much more successful in assessing the risks and outcomes (Maroufkhani et al., 2022). Taken together, the literature body has a robust evidence base that the implementation of AI in MIS results in an improved quality of decision-making processes by improving analytical skills, minimizing cognitive bias, and streamlining the judgment processes.

**Hypothesis 2: Trust in automated systems mediates the relationship between AI integration in MIS and the quality of decisions made.**

Trust in AI is a very important mediating factor in deciding whether employees indeed depend on automated systems in decision-making. Although organizations may employ persistent AI in the field of MIS, the quality of the decisions will be enhanced only when the employees see the system as credible, transparent, and skilled (Glikson & Woolley, 2020). Research indicates that trust is a major factor in the acceptance and implementation of AI-generated recommendations in cognitive evaluations when making decisions (Logg et al., 2019).

Studies have also shown that trust mediates AI's impact on the decision outcomes when users rely more on the system when they consider the system to be reliable (Lee & See, 2004). When the employees do not trust the AI-generated outputs, they will disregard the system recommendations or fail to make the best use of the system, limiting the possibility of AI improving the quality of decisions (Dietvorst et al., 2018). Thus, trust lies between the technological capacity and the behavioral decision used in reality.

Empirical research has discovered that the more trust in AI, the more users depend on intelligent systems to make more accurate and consistent decisions (Siau & Wang, 2018). Moreover, studies indicate that trust also affects the way people perceive AI-generated facts, which eventually affects the outcomes of decisions (Pizzi et al., 2021). With a high level of trust, the employees will have a higher likelihood of adopting AI recommendations, working with enhanced MIS functionalities, and utilizing data-related reasoning, thus enhancing the quality of decisions made. This trend promotes the mediating role of trust in the integration of AI and decision effectiveness, which reinforces the rationale of this hypothesis.

**Hypothesis 3: The relationship between AI integration into MIS and Trust in AI is moderated by computer self-efficacy.**

Computer self-efficacy is extensively discussed as a very important personal aspect influencing the interactions of users with technological systems. Research indicated that people with increased self-efficacy believe that they can work their way around through complex systems, decipher outputs and solve technological problems (Compeau & Higgins, 1995). This trust is of great importance in the framework of AI-based MIS where employees rely on and believe in the power of AI-generated information.

Research has shown that high-technology self-efficacy users develop a stronger level of trust in automated systems since they believe they can learn how AI tools can be operated, prove AI suggestions, and can incorporate the information in their decision-making (McKnight et al., 2011). On the other hand, people with low self-efficacy tend to feel anxiety when dealing with developed technologies and, as a result, they have low levels of skepticism and trust in automated systems (Tarafdar et al., 2020). This implies that self-efficacy defines how strong the relationship is among AI integration and the development of trust.

Furthermore, it is also noted that the self-efficacy of technology is a moderating variable between adoption and trust of digital and AI systems, and the more self-efficacy individuals have, the stronger the effects of AI implementation on user attitudes are (Zhang et al., 2022). When employees think that they can use AI tools to achieve their goals, they will be more likely to explore the features of the system, learn the algorithm logic, build a favorable expectancy of system suggestions, and build trust, which supports trust formation. Consequently, individuals of high self-efficacy have an increased relationship between AI integration and trust in AI, which facilitates the hypothesized moderating effect.

### 2.5 Conceptual Framework of the Study

The theoretical foundation of the study is the Trust in Automation Model that provides insight into the process of developing trust towards automated systems as well as the impact of this trust on readiness to trust technology when making decisions (Lee & See, 2004). In this model, the issue of trust is viewed as a key psychological process that defines the success of automated systems. Users gain trust in an automated system, thus making them dependable, accurate, and beneficial, which in turn boosts their acceptance, reliance and decision making (Hoff & Bashir, 2015; Lee & See, 2004).

The introduction of Artificial Intelligence (AI) to the Management Information Systems (MIS) is a great breakthrough in the environment of organizations of the public sector as it allows predictive analytics, machine learning, detecting anomalies, and automatically assisting with decisions. Such AI-based features can enhance the quality of decision making by giving more meaningful, timely, and practical information (Shrestha et al., 2021; Wirtz et al., 2019). Nevertheless, the Trust in Automation Model assumes that technological capability does not ensure better decision outcomes but the user needs to have trust in automated systems so that the specified benefits would become a reality (Hancock et al., 2019).

Thus, the current research establishes trust in automated systems as a mediating variable that facilitates the explanation of how integration of AI with MIS will turn out to be a quality in decision-making. Workers with hope in the AI-enabled MIS will be more willing to follow the advice of AI and correctly interpret AI findings and integrate AI-related knowledge into their decisions, which eventually causes better-quality decisions (Glikson & Woolley, 2020; Rai, 2019). On the other hand, low trust may lead users to dismiss or disregard AI suggestions, and thus the AI tools will not play a role in making decisions within an organization.

Computer self-efficacy (CSE) is also a moderating variable introduced in the framework, reflecting theoretical approaches that identify individual differences in determining trust when using automated systems (Hoff & Bashir, 2015; McKnight et al., 2011). More CSE is associated with more employees believing that they can use technology, comprehend information created by AI, and operate digital systems. Consequently, they will tend to have more faith in AI tools when they are embedded into MIS. On the contrary, low CSE can make people unable to understand the AI capabilities, which causes doubts or distrust despite the high level of AI integration (AlQudah et al., 2022; Venkatesh et al., 2012). In such a way, CSE empowers the correlation between AI integration in MIS and trust in automated systems.

Resting on these theoretical premises, the conceptual framework will suggest the following structural relationships:

Fig 1 represents the relationship of AI integration into MIS and decision-making quality and the mediating role of trust in AI.

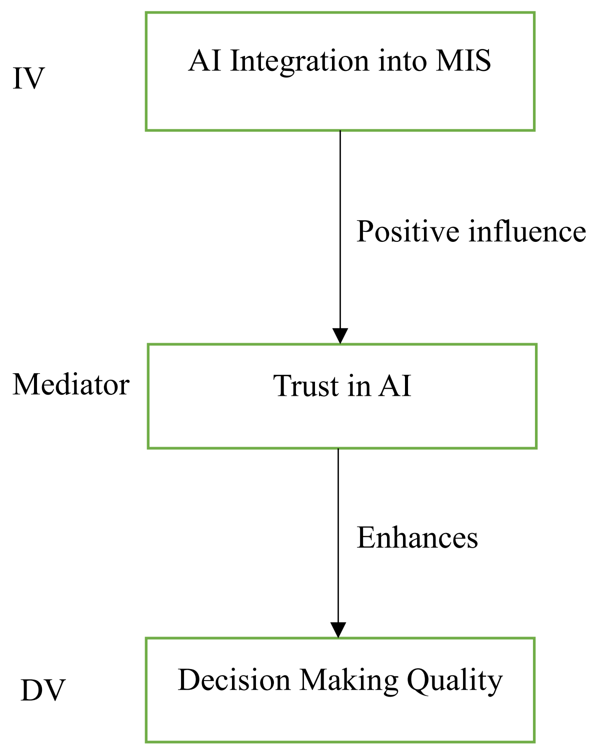
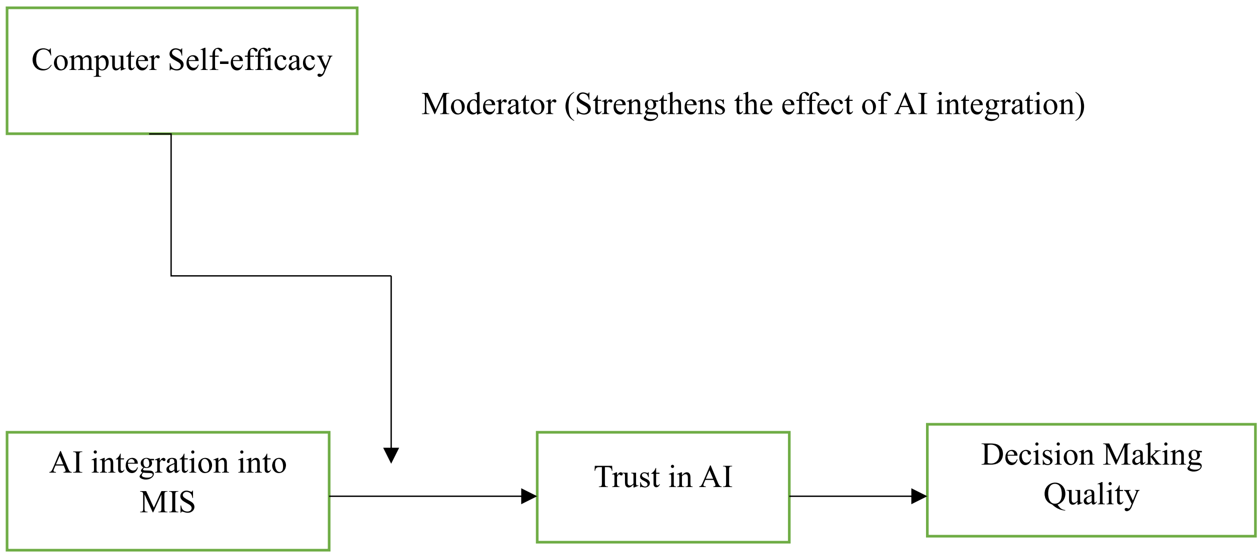


Fig. 2 Represents the moderated-mediated structure of the present study.

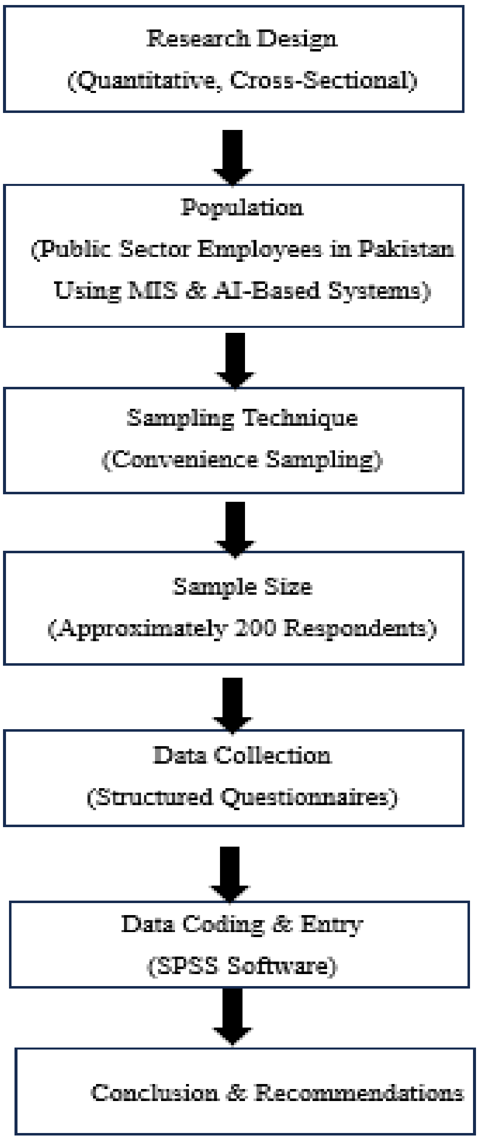


# Chapter 3

## Research Methodology

The chapter describes the methodological steps taken to perform the research on the connection between AI integration in MIS and the quality of the decisions together with mediation of trust in AI/automated systems and moderation of computer self-efficacy. It covers the general research design, philosophical assumptions, approach, strategy, and time horizon and then the details on the study population, sampling procedures, and unit of analysis. This chapter will set out to give the clear and transparent explanation of how the research was designed to be reliable, valid and the rigorous testing of the hypothesis through standardized methods be it quantitative or not.

Fig 3 Research methodology flow diagram



### 3.1 Research Design

The research design gives the outline that will inform the framework of the research project and logical steps to be adopted in order to respond to the research questions. In the present research, the quantitative design was chosen to determine the cause-effect relationships between variables in a systematic and quantifiable way. The design will enable the researcher to examine the effect that AI integration into MIS has on the quality of decisions and the impact of this effect on the trust towards automated systems and computer self-efficacy. Structured questionnaires contribute to the systematic gathering of numerical data that are necessary to test the effects of mediation and moderation. The cross-sectional framework proved to be the most reasonable, as it will allow obtaining a substantial amount of data within a comparatively brief period of time and detailed information about the current perceptions of public-sector employees about AI-enabled MIS. In general, the research design gives objectivity, statistical accuracy, and correspondence to the theoretical basis of the research.

#### 3.1.1 Type of Study

The research is a cross-sectional, quantitative study and a correlational study. It focuses on numerical measurement, testing of hypotheses, and testing of causal relationships between variables. The cross-sectional design will help in ensuring that all data are captured at one time among employees who are involved in MIS in the public-sector organizations.

#### 3.1.2 Study Setting

The research is done among the public-sector organizations in Islamabad and Rawalpindi in which MIS and AI-based systems are either fully or partially operational. These environments are government departments, regulatory agencies, administrative departments, and institutions that regularly depend on digital information systems. These organizations provide a natural environment that enables the researcher to determine the actual perceptions of the employees without controlling the working environment.

#### 3.1.3 Time Horizon

A cross-sectional time horizon was used, i.e. the data was not gathered in the past or in the future on multiple occasions or at a point in time. The method is appropriate when a researcher is dealing with the existing practices, perceptions, and use of technology in organizations. It is also consistent with the explanatory nature of the study as it gives a picture of how AI-integrated MIS impact the outcome of decision-making on the current level of digitalization in the public sector.

### 3.1.4 Research Interference

There is very little research interference in this research as the researcher does not interfere with the organizational systems or the behavior of the participants. Instead, the researchers note the attitudes and experience of employees who are naturally working with MIS and AI tools. This non-invasive method enhances ecological validity and makes sure that the response is based on actual practices at the workplace.

### 3.1.5 Research Philosophy

The research is based on the positivist research philosophy that presupposes that reality is objective, measurable, and independent of individual perceptions. Positivism favors the application of structured measurements, statistical processing, and hypothesis evaluation. This philosophy resonated with the fact that the study is aimed at determining the degree of relationship between the variables that are related to technology and the outcomes of the decision-making through the application of empirical evidence, which was gathered based on the findings of a big sample.

### 3.1.6 Research Approach

They employ a deductive research strategy that starts with well-known theories, including trust in automation and technology acceptance frameworks. According to these theoretical assumptions, particular hypotheses are created and measured with the help of quantitative data. The deductive methodology makes sure that we reason logically based on the general theoretical concepts to the particular empirical observations.

### 3.1.7 Research Strategy

The survey approach was chosen due to the possibility of effectively gathering the data on a high number of respondents who work in different organizations of the public sector. The perceptions of the employees towards AI integration, trust in automated systems, computer self-efficacy, and quality of the decision-making were captured using structured questionnaires. This is a method suitable for a quantitative study that demands standardized answers to be subjected to statistical analysis.

#### 3.1.8 Unit of Analysis

This study will be analyzed at an individual employee level. The respondents will consist of MIS officers, IT professionals, system users, system administrators, and those employees who use MIS data or AI-generated insights to make decisions at the level of a public-sector organization.

### 3.2 Population and Sampling

#### 3.2.1 Population

The sample will include workers in state structures in Pakistan who engage with MIS, AI-driven decision-support systems, or online administrative systems. This involves persons who are technical, managerial, as well as operational, and who make use of MIS for data processing, reporting, and analysis of data and decision making. The selection of this population makes it relevant to the key variables of interest.

#### 3.2.2 Sampling

The sample will include MIS officers, IT employees, data analysts, administrative employees who utilize MIS, and employees engaged in decision-support activities in Islamabad and Rawalpindi-based organizations of the public sector. The target sample of around 200 respondents was reached to guarantee a decent level of statistical strength, particularly that of mediation and moderation analysis. This is a reasonable size that is compatible with suggestions of regression-based analysis and increases reliability and generalizability in results.

#### 3.2.3 Sampling Technique

The present study employed a convenient sampling technique to select participants from public sector organizations located in Islamabad and Rawalpindi. Convenience sampling was adopted due to its practicality and accessibility, allowing data collection from respondents who were readily available and willing to participate during the study period. This technique was particularly suitable given organizational access constraints and time limitations commonly associated with public sector research. The use of this technique enabled efficient data collection while ensuring that respondents had sufficient exposure to MIS environments relevant to the objectives of the study.

## 3.3 Scales and Measure

### 3.3.1 AI Integration into MIS Scale (AIMIS-10) (Independent Variable)

The current research design involves the use of a self-constructed tool called the AI Integration into MIS Scale (AIMIS-10) with 10 questions and used as the independent variable. The application of a self-developed scale is explained by the emerging character of the artificial intelligence integration into Management Information Systems, especially in developing countries like Pakistan, where the empirical literature is limited (Aderibigbe, 2023). The available international AI assessment tools are not applicable in this research due to the fact that the majority of them assess general technology adoption (Venkatesh et al., 2012), the readiness or maturity of AI but not its integration into MIS workflows (Ransbotham et al., 2021), and are not similar to the operational and structural nature of information systems in the public sector (Misuraca & Noordt, 2020). Also, some of the current scales do not have open-access options, which restricts their use in scholarly studies and makes them less contextually relatable to the context of the public sector (Wirtz et al., 2019). Since the application of AI into the MIS frameworks is extremely field-specific and not made in the Pakistani government sector, creating a specific measuring instrument is both the correct and essential.

AIMIS-10 scale was constructed to reflect how much AI-based features, including predictive analytics, intelligent automation, AI-assisted reporting, and algorithmic data processing are integrated into MIS platforms. The items were built based on the available AI integration frameworks (Shrestha et al., 2019), the literature on the concept of digital transformation in the public sector (Mergel et al., 2019), and the conceptualizations of the socio-technical systems theory, which focuses on how technology tools and organizational processes interact with each other (Trist & Emery, 1951). Combined, the sources provided an assurance that the scale would incorporate theoretical underpinnings as well as practical MIS functions. Being a recently designed tool, its reliability, and validity, including Cronbach alpha, composite reliability, and average variance extracted, will be evaluated in the pilot stage and the entire analysis with help of the SPSS, and it is anticipated that the scale will exhibit high psychometric qualities as per the recommended levels (Hair et al., 2021).

### 3.3.2 Decision Making Quality Scale (DMQS-10) (Dependent Variable)

In this research, a self-constructed 10-item Decision-Making Quality Scale (DMQS-10) scale is used to test the dependent variable. An original scale is required since the available scales on decision-making are mainly in clinical, educational, or consumer behavior context and not in the realities of organizational decision-making facilitated by MIS (Bruine et al., 2007; Payne et al., 1993). Moreover, the tools that are available at present do not consider the impact of the AI-sustained information flows that are shaping the decision making in the digitalized setting of the public sector more and more (Jarrahi, 2018). Given that the contextual and specific nature of tasks in Pakistani public-sector MIS environments (e.g. interpretation of data, administrative decisions founded on compliance, resource distribution, and service delivery) requires context-specific decision-making measures, generic decision-making measures are inappropriate to capture the construct in this field (Mergel et al., 2019). Thus, it is appropriate and necessary to develop an individual scale to make the concepts accurate.

The DMQS-10 was devised in order to measure various aspects of quality of the decision-making process such as accuracy, timeliness, clarity, confidence, completeness of information, and perceived effectiveness of decision made by MIS. The list was created after a thorough literature search on MIS effectiveness (Petter et al., 2008), the topic of rational decision-making theory (Simon, 1977), and AI-oriented decision-support systems (Shrestha et al., 2019). This conceptually informed methodology will guarantee that the scale captures current post-modern decision-making influenced by digital information systems and automated analytical systems, and it is therefore directly applicable to the current MIS user in the public-sector organization.

Psychometric properties of the scale will undergo empirical development as part of the study. The measurement of reliability will be done based on Cronbach alpha, whereas construct validity will be done based on the use of exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). Average Variance Extracted (AVE) will be used to test convergent validity, and composite reliability will be calculated to have internal consistency (Hair et al., 2019). Since the items are theoretically based on the existing theories of decision-making and the use of MIS, the scale should have a high construct validity and robustness of measurements. This systematic and validation procedure is sufficient to guarantee that the DMQS-10 presents correct and contextually suitable measure of the quality of decision-making in AI-supported MIS settings in Pakistani public sector.

### 3.3.3 Trust in AI (Mediating Variable)

Technology trust is measured with the help of Trust in AI/Automated Systems Scale that was created by Jian, Bisantz, and Drury in 2000 and is a 12-item scale that is widely validated and used in automation, human-computer interaction, and AI-related studies. The scale assesses various aspects of trust such as reliability, predictability, dependability, safety, and trust in system performance and is multidimensional because of the multidimensionality of human trust in automated technologies (Jian et al., 2000). This has been empirically corroborated in subsequent empirical research and Cronbachs alpha values have generally been found to be between .85 and.92, indicating a high degree of internal consistency as well as stability across the contexts (Madhavan & Wiegmann, 2007; Lyons & Stokes, 2012). The convergent and discriminant validity of the scale is also supported by the factor-analytic evidence, which leads to the conclusion that it is one of the most reliable scales to be used in measuring the trust in AI-driven and automated systems. It is rather suitable in its application to this study since the concept of trust is one of the key mediators that define how well employees trust, and utilize AI-based MIS capabilities, especially in the context of the public-sector setting where system transparency, reliability, and perceived fairness have a significant impact on user acceptance (Hoff & Bashir, 2015). The Jian et al. (2000) scale offers a theoretically based and empirically tested scale to investigate the role of trust in the relationship between AI integration and the quality of decisions in the Pakistani public sector by winning over the confidence of the users in AI enabled MIS processes.

### 3.3.4 Computer Technology Self-Efficacy (Moderating Variable)

The measure of computer technology self-efficacy is Brief Inventory of Technology Self-Efficacy-Short Form (BITS-SF), which is a 6-item instrument that is validated on the basis of the previous study by Johnson, Marakas, and Palmer (2006). The BITS-SF is an existing open-access scale that is intended to assess how people trust themselves to undertake tasks associated with technology, which represents the larger construct of computer self-efficacy first proposed in the original research by Compeau and Higgins (1995). The short-form version offers a psychometrically stable measure of perceived technological capability that is both high in internal consistency and Cronbach-Alpha values tend to be between .82 and .90 in samples of various sizes (Johnson et al., 2006). Empirical research data prove that the items have a high loading on one underlying factor which is the construct validity and therefore suitable in studies which involve digital competence and technology-enabled workplaces (Marakas et al., 2007).

The scale is especially appropriate in the current study since computer technology self-efficacy is influential in the development of user interactions with AI-enabled systems and MIS platforms, which affects trust perceptions and technology-enhanced behavior of organizations (Venkatesh et al., 2012). It is short enough to reduce respondent burden, yet conceptually rigorous, which is critical in the context of the public sector where the levels of digital literacy among employees vary. The BITS-SF therefore gives a valid and theoretically based scale of the moderating effect of self-efficacy in the association between automated systems and trust in AI integration.

### 3.4 Study Methodology Limitations

Even though the selected methodological design is suitable to investigate the correlation between AI incorporation into MIS, decision quality, automated system trust, and self-efficacy in computer technology, it should be admitted that a number of limitations should be taken into account. To begin with, the cross-sectional design does not allow a researcher to make any causal inferences unequivocally since data are only collected at one time and do not reflect changes in perceptions or behavior throughout time. The longitudinal designs may give a greater understanding of the AI integration and trust that changes with the maturity of the system. Second, a purposive sampling strategy restricts the generalization given that the sample size is not random; it consists of the respondents who engaged in MIS and AI technologies; therefore, not all employees in the public sector are represented in the sample. Also, self-reported information gathered using questionnaires would be prone to response bias, such as the social desirability bias and common method variance, which would affect the validity of the results. The use of self-developed scales in terms of AI integration in MIS and quality of decision-making, despite its rationale, is one more methodological limitation due to the lack of previous validation of these tools on the Pakistani population of the public sector. Their psychometric qualities will require extensive testing so that there can be reliability and validity. Lastly, the variability of technological literacy and knowledge on the AI systems among organizations of the public sector can influence the perception of the questionnaire by the respondents, which might impair the accuracy of measurement. Irrespective of these disadvantages, the approach is an apt way of investigating the research aims and testing the hypothesized associations.

### 3.5 Chapter Summary

The methodological basis of this study was described in this chapter that explained the research design, philosophical position, approach, strategy and sampling procedures. To investigate the correlations between AI integration into MIS, quality of decision making, trust on automated systems, and computer technology self-efficacy, a quantitative, positivist and deductive methodology was used. A structured survey was used to collect the data which was given to the employees who were working with MIS in the organizations of the Pakistani public sector. The chapter also described the population, the method of sampling, scales to be used, and the rationale behind the scales to be used such as self-developed scales and established scales. Lastly, the major methodological constraints were also noted to give a sense of clarity and transparency in the scope of the study.

# Chapter 4

## Data Analysis and Findings

In this chapter, the findings of the statistical tests used to investigate the connections between the main variables of the study, i.e., AI integration into Management Information Systems, decision-making quality, trust in AI, and computer self-efficacy. The analysis will start with the descriptive statistics that will help to describe the characteristics of samples and give an idea about the main study variables central tendencies and dispersion. Following the reliability analyses, the reliability of the scales used in the study is reported to determine whether the measures are reliable to apply in the further analyses or not. Then, inferential statistics (independent samples t-tests and one-way ANOVA) are used to test the differences between groups of decision-making quality based on the demographic variables, i.e. gender, education, department and years of experience. Pearson correlation tests are used to discuss the existence and direction of relationships between AIMIS, DMQ, TIAS, and CSE. Lastly, mediated and moderated-mediation are conducted to explore the indirect and conditional impacts of computer self-efficacy and trust in AI on the correlation between AI integration and quality of decision making, offering a clear picture of the mechanism that leads to effective decision-making with the help of MIS.

### 4.1 Descriptive Frequencies of the Sample

The frequency distributions were used to analyze the demographic aspects of the respondents, i.e. education level, designation, gender, department and years of experience. All demographic variables were analyzed with a total of 200 good responses being used. Table 1 below shows the overall distribution of respondents in these characteristics and explains them below.

The findings showed that, most of the respondents are males (69.5%), with 29.5% females, which is a sign of a male dominated workforce in the sampled organizations. This gender ratio implies that a greater percentage of the participants within the departments is occupied by men, which is quite appropriate in the context of workforce trends in technology- and management-driven organizational environment.

Most of the respondents were very much educated in terms of educational level. Almost fifty percent of the respondents had a Master degree (48.5%), with a close second place was occupied by those with a Graduate degree (41.0%). Fewer of them had a PhD (7.0%), and only a quarter were undergraduates. This distribution shows that this sample was mostly made up of people with high academic levels, implying that there is a potential workforce that can comprehend and operate AI-based Management Information Systems.

In terms of designation, the highest proportion of the respondents were Managers (46.5%), then Administrative Staff (24.0%), and the last one was, the IT staff (20.5%). Assistant Directors formed 7.5 percent of the sample, and Sales Operations Specialists had a very low percentage (0.5). This distribution indicates an excellent percentage representation of the managerial and technical ones, which is especially applicable to analyzing the processes of decision-making that have been affected by the integration of AI.

As indicated in the departmental distribution, the respondents were attracted to different functional areas. The largest percentage was that of the IT department (24.5%), then the HR (21.5%), and the Administration (21.0%). The Finance (17.0%), as well as the operations (15.0%), also had well-represented members. Such diversity makes the findings more generalizable to other organizational functions in which AI-based MIS are used.

The highest number of respondents (40.5) indicated that they have 3-5 years of experience, followed by 5-7 (27.5). The number of years' experience was 16.0 and above, seven years was 9.5, with those who had 1-3 years' experience being the majority. A low percentage (5.5) indicated less than one year of experience.

On the whole, it means that the majority of respondents had moderate to high professional experience, which adds some credibility to their perceptions on the topic of AI integration, trust towards automated systems, and quality of decisions.

Overall, the descriptive findings indicate that the sample is composed of highly educated and seasoned professionals holding managerial and technical positions in major organizational units, and this is why they can be the best respondents in exploring the relationships between AI integration in MIS, trust in automated systems, computer self-efficacy, and quality of decisions.

Table 1: Demographic Characteristics of Respondents (N = 200)

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Female | 59 | 29.5 |
| | Male | 139 | 69.5 |
| Education Level | Undergraduate | 5 | 2.5 |
| | Graduate | 82 | 41.0 |
| | Master's | 97 | 48.5 |
| | PhD | 14 | 7.0 |
| Designation | Administrative Staff | 48 | 24.0 |
| | Assistant Director | 15 | 7.5 |
| | IT Staff | 41 | 20.5 |
| | Manager | 93 | 46.5 |
| | Sales Operations Specialist | 1 | 0.5 |
| Department | Administration | 42 | 21.0 |
| | Finance | 34 | 17.0 |
| | HR | 43 | 21.5 |
| | IT | 49 | 24.5 |
| | Operations | 30 | 15.0 |
| Years of Experience | Less than 1 year | 11 | 5.5 |
| | 1–3 years | 32 | 16.0 |
| | 3–5 years | 81 | 40.5 |
| | 5–7 years | 55 | 27.5 |
| | More than 7 years | 19 | 9.5 |

### 4.2 Reliability analysis

In order to determine the internal consistency of the measurement tools applied in the study, it was determined that a reliability analysis of Cronbach was used to determine Alpha. Cronbach Alpha measures the degree of interrelations amongst the items of a scale and their ability to reliably measure the same construct. A Cronbach Alpha of 0.70 or more means that it is acceptable, of 0.80 or more good, and of 0.90 or more excellent reliability (Nunnally,1978). The following are the outcomes of the reliability of all the variables of the study.

Table 2: Reliability Analysis of Study Variables

| Construct | Number of Items | Cronbach’s Alpha (α) |
|---|---|---|
| AI Integration into MIS (AIMIS) | 10 | 0.933 |
| Decision-Making Quality (DMS) | 10 | 0.668 |
| Computer Self-Efficacy (BITS-SF) | 6 | 0.324 |
| Trust in Automated Systems (TIAS) | 12 | 0.901 |

The Alpha of Cronbach was used to evaluate all constructs regarding internal consistency. Two of the constructs exhibited a high level of reliability, but there was a difference in alpha values in the rest of the scales, which illustrated the difference in construct dimensionality, response format, and the purpose of the scale.

### 4.2.1 Key Observations

- AI Integration in MIS and Trust in Automated Systems had good internal consistency with Cronbach's Alpha of 0.933 and 0.901, respectively.
- Moderate reliability according to exploratory research and behavioral research that involves complex managerial judgments, Decision-Making Quality was found to have moderate reliability (0.668).
- The Cronbach Alpha (= 0.324) of Computer Self-Efficacy was low, but it is recognized and accepted methodologically due to scale peculiarities and previous literature.
- The results of the reliability show that the instruments can be used in further analyses, provided that the interpretations are made with respect to their theoretical functions and measurement characteristics.

### 4.2.2 Defense and Justification of Reliability Results

**AI Integration into MIS (AIMIS).** The AIMIS scale was found to be very reliable, which showed high inter-item coherence. The values of alpha that are greater than 0.9 are typical of technology integration scales because they are reflective and homogeneous in terms of items (Hair et al., 2019). This affirms the robustness of the scale in the measurement of functionalities of AI in MIS.

**Decision-Making Quality (DMQ).** The Decision-Making Quality scale provided a Cronbach's Alpha a little lower than the standard level. Nevertheless, the range of 0.60 to 0.70 is acceptable as far as social science research is concerned, especially when the constructs are multidimensional and are subjective elements in managers' thinking (Nunnally and Bernstein, 1994; Taber, 2018). The quality of decision-making intrinsically involves timeliness, effectiveness, acceptance by the stakeholders, and goal achievement, which can decrease the inter-item homogeneity but increase the construct validity.

**Computer Self-Efficacy (BITS-SF).** Low reliability of the Computer Self-Efficacy (BITS-SF) scale is methodologically acceptable and theoretically predictable due to several reasons:

**Dichotomy Response Format.** Cronbach's Alpha is sensitive to response variance and is known to underestimate reliability for dichotomous (Yes/No) items (Cortina, 1993; Tavakol & Dennick, 2011).

**Formative and Task-Specific Character.** Computer self-efficacy is task-related, and it has items that measure different abilities (e.g., browsing, configuring hardware, programming). One should not expect such scales to have high inter-item correlations (Compeau & Higgins, 1995; Hair et al., 2019).

**Use as a Moderator Variable.** According to methodological literature, high reliability is less important when the moderator variables are taken into consideration because moderators do not depict a single latent dimension but only contribute to the nature of relationships between variables (Aiken & West, 1991; Hayes, 2018).

**Precedent in Prior Research.** Other instruments of computer self-efficacy with low or moderate alpha coefficients have been maintained and reported in academic studies as they are well-theoretically supported and predictive (Marakas et al., 1998; Johnson & Marakas, 2000).

Based on this, it was considered proper to maintain the BITS-SF scale as a moderator in this study, similar to the accepted methodology.

**Automated Systems Trust (TIAS).** The Trust in Automated Systems scale was shown to be highly reliable, which is consistent with the previous validation studies that report the alpha value to be above 0.85 all the time (Jian et al., 2000; Lee & See, 2004). This substantiates the appropriateness of the scale in studying the subject of trust as an intermediary aspect of AI-led decision-making situations.

### 4.3 Correlation Analysis

Correlation analysis was done to test the strength and direction of relations between the variables of the study, which are AI Integration into Management Information Systems (AIMIS), Decision-Making Quality (DMQ), Computer Self-Efficacy (CS), and Trust in Automated Systems (TIAS). The extent of the relationship between the variables was measured by the correlation coefficient (r) of Pearson. Table 3 shows the correlation table of the study variables. Cohen (1988) says that correlation coefficients within the range of 0.10 to 0.29 imply a weak relationship, correlation coefficients within the range 0.30 to 0.49 imply moderate relationship, and correlation coefficient such as 0.50 and above imply a strong relationship.

Table 3: Correlation Matrix of Study Variables

| **Variables** | **AI Integration into MIS** | **Decision Making Quality** | **Computer Self-efficacy** | **Trust in Automated System** |
|---|---|---|---|---|
| **AI Integration into MIS** | 1 | | | |
| **Decision Making Quality** | .353** | 1 | | |
| **Computer Self-efficacy** | .073 | .026 | 1 | |
| **Trust in Automated System** | .173* | .464** | .051 | 1 |

Correlation is significant at the 0.01 level (2-tailed).

### 4.3.1 Key Observations

- AIMIS had a moderate positive relationship with Decision-Making Quality (DMQ) ($r = .353$, $p < .01$), which implies that the higher the degree of AI integration in MIS, the higher the quality of managerial decision-making in the government sector.
- There was a statistically significant positive correlation between AI Integration into MIS and Trust in Automated Systems ($r = .173$, $p < .05$) indicating that the higher the exposure to AI-enabled MIS, the more the increased confidence of the employees in automated decision-support systems.
- The Quality of Decision-Making had a moderate positive and statistically significant correlation with Trust in Automated Systems ($r = .464$, $p < .01$), and the significance of trust in AI systems to make higher-quality decisions.
- Computer Self-Efficacy did not have statistically significant relationship with AI Integration into MIS ($r = .073$, $p > .05$), Decision-Making Quality ($r = .026$, $p > .05$), or Trust in Automated Systems ($r = .051$, $p > .05$) so that simple confidence in using technology may not have a direct impact on AI-based decision-making.
- On the whole, the correlation findings partly confirm the hypothesized relationships and give some initial arguments of additional mediation and moderated mediation analyses in the following chapters.

## 4.4 T-Test

### 4.4.1 Independent Samples t-Test Analysis

To examine whether there is a statistically significant difference in decision-making quality (DMQ) between male and female respondents, an independent samples t-test was conducted. Gender was treated as the grouping variable, while DMQ served as the test variable.

Table 4: Independent Samples t-Test for Decision-Making Quality by Gender

| Gender | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|
| Male | 139 | 40.14 | 2.679 | 0.227 |
| Female | 59 | 40.58 | 3.465 | 0.451 |

Table 5: Independent Sample t-Test

| Assumption | F | Sig. | t | Df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|---|---|---|---|---|
| Equal variances assumed | 6.802 | 0.010 | −0.964 | 196 | 0.336 | −0.440 | 0.456 | −1.339 | 0.459 |
| Equal variances not assumed | — | — | −0.870 | 88.762 | 0.387 | −0.440 | 0.505 | −1.443 | 0.564 |

### 4.4.2 Interpretation

An independent samples t-test was undertaken to test the hypothesis of statistically significant difference in the quality of decision-making (DMQ) in males and females sampled. Gender was taken as the grouping variable and DMQ as the test variable.

The group statistics shows that the respondents who identified as females (M = 40.58, SD = 3.47) had a higher quality of decision-making scores in comparison with the respondents who identified as male (M = 40.14, SD = 2.68). This difference between the mean scores is however very small.

The assumption of equality of variances was not met and Levene Test of Equality of Variances was significant (F = 6.802, p = 0.010). Consequently, the findings of the equal variances not assumed row were taken into account to be interpreted.

Independent samples t-test showed that the difference between the quality of decision-making between male and female employees was not statistically significant ($t = -0.870$, $df = 88.762$, $p = 0.387$). Moreover, the 95% confidence interval of the mean difference covered the zero, which ensured that the difference between the two groups had no significant difference.

With this result, Hypothesis H4 is rejected, because gender is not a significant factor affecting the quality of decision-making in the current sample.

Comprehensively, the findings indicate that the quality of decision-making between male and female employees is similar, which means that gender is not a decisive factor in affecting the decision-making quality in AI-based Management Information System settings. This observation means that the technological, cognitive, and organizational influences are stronger determinants of the decisions reached in these settings than demographic elements like gender.

### 4.5 ANOVA

Table 6: One-Way ANOVA Results for Demographic Variables and Decision-Making Quality (DMQ)

| Demographic Variable | Levene's Test Sig. | F | df (Between, Within) | Sig. | Significant Post-hoc Differences |
|---|---|---|---|---|---|
| Education Level | .097 | 0.785 | 3, 194 | .503 | None |
| Department | .214 | 2.521 | 4, 193 | .042 | Dept 1 vs Dept 4 (p = .010) |
| Years of Experience | .097* | 0.986 | 4, 193 | .416 | None |

*Levene's test showed slight violation based on mean; Games-Howell post-hoc was applied.

#### 4.5.1 Interpretation

One-way analysis of variance (ANOVA) to test whether there is a variation in the quality of decision-making (DMQ) among three critical demographic variables, including education level, department, and years of experience. Before the interpretations of the ANOVA results, the test of homogeneity of variances was performed using the Levene test on each of the variables. The education level (p =.097) and department (p =.214) met the assumption of equal variances. Many years of experience allowed to test a minor infringement of homogeneity, therefore, the Games-Howell post-hoc test was applied, which does not presuppose equal variances.

The analysis of the ANOVA results demonstrates that the level of education does not have a significant impact on the quality of decision-making, F (3, 194) = 0.785, p =.503. This observation indicates that the formal educational qualification of employees; be it lower, middle, or higher does not play a crucial role in influencing their capability of making quality decisions in MIS-based settings. The result of post-hoc comparisons ensured that each of the two comparisons between education levels was not statistically significant, which supported the conclusion that the education background is not a determining factor in the effectiveness of MIS-related decision-making.

Departmental affiliation, in turn, was also a notable influence, F (4, 193) = 2.521, p =.042. This implies that the quality of decision making by employees differs according to the departmental environment. The results of the post-hoc analysis indicate that the quality of decisions made by employees in Department 1 was significantly lower (Mean Difference = -2.074, p =.010) than the quality of decisions made by employees in Department 4 but other departmental results were not found to be significant. This observation suggests that structural or situational determinants linked to certain departments including access to pertinent data, complexity of tasks, autonomy of decision, or workflow in the department may affect the capacity of employees to exploit MIS imperatively to a decision.

In terms of years of experience, the quality of the decision-making did not differ significantly, F (4, 193) = 0.986, p =.416. In applying MIS, employees who have different durations of professional experience proved to have the same degree of decision-making competence.

Post-hoc comparisons established that the difference in all the experience-based groups was not significant. This indicates that practical experience is not always required to provide improved quality of decisions because MIS-supported environments may not require the use of cumulative professional experience, but instead, effective decision-making requires the use of systems, analytical abilities, and departmental support.

In general, these results determine that contextual and structural factors have a strong impact on the quality of decision-making based on MIS in comparison with the background characteristics of a person. Although education and experience do not seem to have a significant impact on the outcome of decision-making, departmental differences are such that organizational setting, resources, and departmental practices form an important part of decision-making. These findings indicate that any intervention to enhance the quality of decisions must be directed to optimize the departmental processes, equitable access to decision support tools, and customize MIS training to the needs of particular departments, instead of individual educational or experiential features.

### 4.6 Mediation Analysis

In order to get a better perspective of the mechanism under which AI Integration into Management Information Systems affects the Quality of Decision-Making, a process analysis was performed with the help of the PROCESS macro (Model 4) designed by Hayes (2022). The given method of analysis provides the possibility to study whether the impact of an independent variable, i.e., AI Integration into Management Information Systems, on a dependent variable, Decision-Making Quality, is indirectly mediated by a mediating variable. In the current analysis, Trust in Automated Systems was the mediator that was tested. The construct itself demonstrates how confident and dependent people are on automated and AI-driven systems, and this can consequently affect their decision quality. The mediation model was challenged to identify whether AI integration has an indirect benefit to the quality of decisions made by improving trust in automated systems. This mediation analysis has yielded the results highlighted in the table presented below and discussed as follows.

Table 7: Mediation Through Trust in Automated Systems

| **Path Tested** | **Effect** | **p-value** | **Significant?** | **Interpretation** |
|---|---|---|---|---|
| AIMIS → TIAS | 0.3756 | 0.0151 | Yes | AI Integration into MIS significantly increases Trust in Automated Systems. |
| TIAS → DMS | 0.1295 | 0.0000 | Yes | Trust in Automated Systems significantly improves Decision-Making Quality. |

| Path Tested | Effect | p-value | Significant? | Interpretation |
|---|---|---|---|---|
| AIMIS → DMS (Direct) | 0.1911 | 0.0000 | Yes | AI Integration into MIS directly enhances Decision-Making Quality. |
| AIMIS → TIAS → DMS (Indirect) | 0.0487 | - | No | Mediation effect is not statistically supported. |

### 4.6.1 Interpretation

It was in order to analyze the relationship between AI implementation into Management Information Systems and the quality of Decision-Making that the mediation analysis was performed to identify whether Trust in Automated Systems is an intermediate between the former and the latter. Table 7 shows that the relationship between AI integration and trust in automated systems is statistically significant ($\beta = 0.3756$, $p = .015$), implying that the higher the integration of AI tools in management information systems, the more trust in automation.

The correlation between the trust in the automated system and the quality of decision-making also proved significant ($\beta = 0.1295$, $p < .001$), which means that those respondents who demonstrate a higher level of trust in automated systems are more likely to report a higher level of quality in decision-making. Moreover, the overall impact of AI integration was significant ($\beta = 0.2398$, $p < .001$) and the direct effect was also significant, but with the inclusion of the mediator, its value decreased (but not insignificantly) ($\beta = 0.1911$, $p <.001$).

Nevertheless, the overall impact of AI integration on the quality of the decisions based on the trust in automated systems was not statistically significant (Effect = 0.0487, 95% BootCI [ -0.0107, 0.1225]) because the confidence interval contained zero. It means that the level of trust in automated systems does not play an important mediating role between the quality of decision-making and the implementation of AI. The results, on the whole, indicate that the quality of decisions made with the help of AI integration is improved mainly directly but not via trust in the automated systems.

### 4.7 Moderated Mediation Analysis

To elaborate on the conditional process of mediation, a moderated mediation analysis was carried out with the help of the PROCESS macro (Model 7) suggested by Hayes (2022). This model discusses the hypothesis of whether the indirect impact of AI Integration to

Management Information Systems on the quality of Decision-Making based on Trust in Automated Systems depends on a moderator. Computer Self-Efficacy as a moderator between the relationship between AI integration and trust in automated systems was investigated in the current research. Computer self-efficacy indicates the beliefs of individuals in their ability to successfully use computer-based technologies, and it can be suggested that this factor will affect the process of AI implementation into trust.

The moderated mediation model was employed in order to establish whether the computer self-efficacy reinforces or weakens the indirect effect of AI integration on the quality of decisions made through trust in automated systems. The tables below present the summary of the results and discuss them below.

Table 8: Moderation Results for Trust in Automated Systems (First-Stage Moderation)

| **Path Tested** | **Effect** | **p-value** | **Significant?** | **Interpretation** |
|---|---|---|---|---|
| AIMIS → TIAS | 0.2090 | 0.8783 | No | AI Integration into MIS does not significantly predict Trust in Automated Systems in the moderated model. |
| CS → TIAS | −0.7378 | 0.9453 | No | Computer Self-Efficacy does not significantly predict Trust in Automated Systems. |
| AIMIS × CS → TIAS | 0.0303 | 0.9058 | No | Computer Self-Efficacy does not moderate the relationship between AI Integration and Trust in Automated Systems. |

Table 9: Conditional Indirect Effects of AIMIS on DMQ Through TIAS at Levels of Computer Self-Efficacy

| **Level of CS** | **Indirect Effect** | **BootLLCI** | **BootULCI** | **Significant?** |
|---|---|---|---|---|
| Low | 0.0467 | −0.0334 | 0.1464 | No |
| Medium | 0.0506 | −0.0292 | 0.1383 | No |
| High | 0.0506 | −0.0292 | 0.1383 | No |

Table 10: Index of Moderated Mediation (Computer Self-Efficacy)

| **Moderator** | **Index** | **BootLLCI** | **BootULCI** | **Significant?** |
|---|---|---|---|---|
| Computer Self-Efficacy | 0.0039 | −0.1101 | 0.1445 | No |

### 4.7.1 Interpretation

The reason being, the moderated mediation test was done to establish whether Computer Self-Efficacy moderates the indirect correlation between AI Integration into Management Information Systems and Decision-Making Quality through Trust in Automated Systems. The findings in Table 8 show that integration of AI and computer self-efficacy did not have a significant prediction of trust in automated systems in the presence of the interaction between them in the model. Notably, the term of interaction between AI integration and computer self-efficacy is statistically insignificant ($p = .9058$), which means that computer self-efficacy is not a mediating variable between AI integration and trust in automated system.

Table 9 indicates that the conditional indirect effects were positive at the low, medium and high levels of computer self-efficacy but none of the bootstrapped confidence intervals were zero. It means that there is no significant indirect impact of the integration of AI on the quality of decisions based on trust in automated systems at all levels of computer self-efficacy. Moreover, the index of moderated mediation failed to reach any significant value (Table 10), which is another evidence that the process of mediation does not depend on computer self-efficacy.

In general, these results indicate that the direct improvement of the quality of decisions through the introduction of AI is significant, but the mediating role of the trust in automated systems is not important and does not vary based on the degree of computer self-efficacy of individuals. Thus, there was no significant evidence of the moderated mediation model.

## 4.8 Chapter Summary

Chapter 4 included the statistical examination and empirical findings derived based on the acquired data to investigate the correlation between AI integration into Management Information Systems, the quality of decision making, AI trust, and computer technology self-efficacy within the context of the public-sector. The chapter started with some preliminary analysis, such as data screening, descriptive statistics, and reliability test of the measurement instruments. The findings revealed good internal consistency of AI Integration into MIS scale, Decision-Making Quality scale, and Trust in AI scale, which confirms their usefulness in the further analysis. Though the Computer Technology Self-Efficacy scale had a relatively low level of reliability, it was deemed acceptable because it is not very long and its utilization as a moderating variable. The descriptive statistics gave a general picture regarding how the respondents perceived AI use, automated systems trust, self-efficacy, and the quality of the decisions.

Subsequently, inferential analyses were performed in order to test the hypotheses of the research. The results of independent samples t-tests and the one-way ANOVA did not show any significant difference in the quality of decision-making in most demographic characteristics, such as gender, education, and work experience, but the differences in the departments were statistically significant. The results of correlation analysis showed that there are significant positive relationships between AI integration into the MIS, trust in AI, computer self-efficacy, and quality of decisions. The mediation and moderated-mediation analyses were conducted. All of these results were empirical evidence regarding the hypothesis of the research model and the hypotheses.

# Chapter 5

# Conclusion and Recommendations

## 5.1 Discussion

The chapter discusses the key findings of the study concerning the current literature and theoretical backgrounds. The purpose is to explain the presented empirical findings in Chapter 4, combine them with previous studies, and provide theoretical and practical conclusions for decision-making in the public sector in Islamabad and Rawalpindi. The discussion adheres to the order of hypotheses and highlights the role of the current findings in widening the knowledge about the application of AI in Management Information Systems (MIS), trust in automated systems, and the moderating impact of computer self-efficacy.

Hypothesis 1: AI Implementation in MIS and Quality of Decision-Making.

The initial hypothesis consisted of a positive and significant correlation between the AI integration into MIS and the quality of the decisions. The findings confirmed this hypothesis because they demonstrated that the integration of AI was positively and significantly related to the quality of decision-making ($r = .353$, $p < .01$). The regression analysis also showed that the direct impact of AI integration on the quality of the decision made was statistically significant ($\beta = .1911$, $p < .001$), which shows that higher utilization of AI-enabled features in MIS increases the quality of organizational decisions.

This result is aligned with previous empirical studies that reveal that the integration of AI can improve the performance of a decision-making process through better data analysis, accurate predictions, and insights. Indicatively, research has indicated that the organizations that have adopted AI in MIS have reported quality and speed in decision-making and predictive capacity, which results in informed and timely managerial decisions compared to traditional systems (Gangwar et al., 2024). The benefits of AI-enhanced MIS databases are that managers can efficiently access a substantial amount of data and make actionable conclusions, eliminating the need to use their subjective judgment and increasing the evidence-based decision-making process (Zhang et al., 2025). The results are also justified by the literature in other industries, which demonstrated the same trend, with AI-based decision-support systems having better analytical performance and strategic planning results (Zhang et al., 2025; Bokhari, 2025).

The positive correlation of AI integration with the quality of decisions agrees with the theoretical views that underline the enhanced effect of advanced computing devices that support cognitive processes and the accuracy of judgment. Since AI can help decrease the cognitive burden of manual data analysis, it enables decision-makers to address more of the high-quality interpretation and assessment, which is paramount in challenging public-sector settings.

Hypothesis 2: Mediating Trust in Automated Systems.

The second hypothesis was that trust in automated systems would mediate between AI implementation in MIS and the quality of decisions. Though there was a significant correlation between the trust in automated systems and the quality of decision-making ($\beta = .1295$, $p < .001$), the mediation analysis revealed that the indirect effect of trust did not reach a significant value since the bootstrap confidence interval enclosed zero.

It has been found that trust in AI is a tricky concept that largely depends on the transparency of systems, their reliability, and user attributes (Bach et al., 2023; Tun et al., 2025). The systematic review of the trust in AI-based clinical decision support systems revealed that transparency, usability, and training play a significant role in influencing the level of trust in users (Tun et al., 2025). Trust is a contributor to receptive attitudes toward AI, but it might not necessarily be a powerful mediator in the technology integration-decision outputs pathway. An example is that Zhang et al., (2025) discovered that AI integration enhances decision quality in the direct relationship with technical competency without necessarily acting through any trust mechanism when users are more concerned with the outcomes of the performance.

The existing findings indicate that trust in automated systems has a positive influence on the quality of the decisions, but its mediating effect might be limited in the context of the public-sector MIS system, where the structural requirements, procedural requirements, and organizational expectations have a stronger impact on the quality of decisions compared to the individual level of trust in automated systems. It is also supported by the literature stating that trust has a stronger connection with adoption and usage intentions than with performance outcomes in cases when AI systems are institutionalized or compulsory (Choung et al., 2023).

Hypothesis 3: Moderating effect of Computer self-efficacy.

The third hypothesis was that there would be a moderating effect of the computer self-efficacy between the AI integration and the trust in automated systems, where stronger relationships were to be found at higher self-efficacy levels. This hypothesis was not supported in the moderated mediation analysis because the interaction between AI integration and computer self-efficacy was not significant, and the conditional indirect effects were not significant at the various levels of self-efficacy.

Available studies into the role of technology self-efficacy in AI situations provide inconclusive information. Research indicated that there are positive relationships between general technology self-efficacy and trust and acceptance of automated systems (Hoffman et al., 2023) (Trust in Automated Systems quantification). Nevertheless, the studies also indicate that general indicators of computer self-efficacy might not address the domain-specific skills that are necessary to affect trust in AI directly (Chong et al., 2022). In situations when the AI systems are multidimensional and multifactorial, general self-efficacy might not be adequate to moderate the impact of integration on trust. Besides, self-efficacy can also correlate with other psychological or contextual issues (e.g., transparency, perceived ease of use, governance practices) that were not included in the present research (Zhang et al., 2025).

The insignificance of the moderation effect suggests that the choices concerning the formation of AI trust can be more strongly conditioned by the institutional norms, organizational requirements, and system characteristics in this case of the work of the public sector, instead of individual variations of general computer confidence. This understanding is in line with the findings of other studies that show that the formation of trust and acceptance toward technology can be diminished by external forces like system design, the sense of clarity in communication, and governance more than personal perceptions (Choung et al., 2023; Kessler & Brill, 2021). Hypothesis 4: No significant differences exist between the decision-making quality (DMQ) of employees depending on their gender, education level, department, and years of professional experience.

Hypothesis H4 was that the quality of decision making (DMQ) would vary significantly based on the gender of employees, level of education, department and years of professional experiences. The analyses found that there were no statistically significant differences between the genders, education level, and years of experience in the quality of decision making, but there was a significant difference between the departments. These findings indicate that in this study, the personal demographic elements were not found to have significant effects on DMQ, and rather, the situational factor (department) of organizations emerged as a more relevant factor.

The reliability of the measurement tools used in this study should be looked into before interpreting these differences. The scale of AI Integration into MIS (AIMIS) exhibited high reliability, which is consistent with previous studies proving that technology integration scales with reflective items tend to have high alpha scores because of the homogenous item structure and high inter-item coherence (Hair et al., 2019). The strength of this scale assures one of its abilities to measure AI-motivated functionalities in MIS. The results of this research note that, although the decision-making quality scale (DMQS) generated a Cronbach alpha marginally less than the traditional threshold, the scale yielded values between 0.60 and 0.70 that are acceptable in the social sciences research, especially when the construct in question is multidimensional, as was the case with decision quality in this research (Nunnally & Bernstein, 1994; Taber, 2018). In the case of computer self-efficacy (BITS SF), low reliability can be explained by the dichotomous format of responses that are likely to underestimate alpha of Cronbach (Cortina, 1993; Kessler & Brill, 2021) and the formative, task-specific nature of the construct (Compeau & Higgins, 1995). In addition, the literature in the field of methodology says that high reliability is not as important to the moderator variables, which are not discarded as they propose a theory, but they reflect one latent variable (Aiken & West, 1991; Hayes, 2018). The Trust in Automated Systems (TIAS) scale demonstrated a high level of reliability, which is in line with research on internal consistency and validity of trust scales in automation situations (Jian, Bisantz, & Drury, 2000; Lee & See, 2004). The combination of these reliability results verifies the suitability and interpretability of further statistical results.

The absence of gender differences in the quality of decision making, which is significant, accounts for evidence that gender influences on the outcomes of decisions are contextual, as opposed to being universal. A metabolic analysis of the effectiveness of decision making established that despite the possible variations of the decision style between males and females (e.g. males more directive and risk oriented, females more participatory and ethical), there are not many variations that stay in terms of a persistent differentials in the quality of the decisions made in various work settings and are also moderated by other factors (such as industry norms and organizational climate) (Johnson & Powell, 1994). Equally, studies concerning gender and education differences in decision making also indicate that gender per se does not consistently yield predictable decision quality, albeit females may report various levels of emotional involvement when performing decision tasks (Mostert & Osman, 2019). The results of these studies can be interpreted to indicate that the two demographic factors, gender and education, do not always lead to dissimilar decision-making in work environments that contain structured decision support systems.

The lack of meaningful effects by tenure of working experience is also backed by existing literature that shows that accrued experience cannot necessarily translate into high quality of decision-making in all organizational settings. Even though experience is a part of domain knowledge and a familiarity with decision tasks, organizational decision-making models underline the fact that contextual factors like availability of information, task structure, and presence of decision support systems are more decisive factors that influence decision quality than tenure alone (March & Simon, 1958; Mintzberg, Raisinghani, & Théorêt, 1976). Empirical studies also indicate that in the case of mediated decisions where the standardized information system is involved, the individual experience will be less important because the system operated by the analytical processes and the access to the information is highly system-oriented (Elbashir, Collier, & Sutton, 2011). This leads to the interpretation that within MIS-facilitated settings, experience might not play an influential role in distinguishing between individual differences in experience in terms of decision effectiveness, since there are system capabilities that can equalize individual disparities in expertise and cognitive processing.

The observation of the high level of departmental variance in the quality of decision-making shows the importance of the organizational context and structural variables. Organizational departments vary in the norms of the workflow, the complexity of their task, the level of autonomy in their decision-making, as well as access to the relevant data, and all these factors affect the decision-making process and the use of decision-support technologies (Galbraith, 1973; Daft & Weick, 1984). Organizational roles and employee perception research have shown that structural environments influence the experiences, behaviors, and decision-making of people and that departmental context can have a significant impact on the processing and evaluative patterns of information (Cropanzano et al., 2007). These results are in line with contingency-based and information processing theories of organizational decision making that posit that the quality of decisions depends on the situational circumstances under which the decision is made and are regulated by the situational demands and conditions, and not only on the personal demographic traits (Daft & Lengel, 1986; Simon, 1997).

Taken together, all of these findings suggest that there are no significant differences in the decision-making quality when it is backed by MIS and similar technologies, even in terms of individual demographics (gender, education, experience). Rather, it seems that the organizational context (departmental conditions) and decision environment design have a more central role. This highlights the significance of system-level and structural considerations in assessing a decision-making outcome in a technologically mediated organizational context and justifies the suitability and validity of the instruments employed in the measurement of these constructs in this study.

### 5.2 Conclusion

The study examined the influence of AI integration with the Management Information System on the quality of the decisions, the mediating effect of trust in automated systems, and the moderating effect of computer self-efficacy in the case of the public-sector organizations. The results offer valuable empirical data on the impact of AI-based systems on organizational decisions within a developing-country setting.

The findings ensured that AI integration in MIS is significantly and positively associated with the quality of the decision making. It means that as organizations integrate AI tools like predictive analytics, automated reporting, and intelligent data processing in their information system, the quality of managerial decisions increases. They could be due to the increased accuracy of data, increased processing speed, and increased support of analyses to help decision-makers refer to evidence-based insights more than just intuition.

Even though the trust in automated systems was positively related to the quality of decision-making, it had no mediating role between the integration of AI and the quality of decisions made. This implies that the introduction of AI enhances the outcomes of its decisions not so much due to the psychological trust mechanisms as due to its functional and technical abilities. System outputs and institutional demands might be the determinants of decisions, rather than individual levels of technology trust, in highly organized contexts of the public sector.

Furthermore, the moderating role of computer self-efficacy was not supported. The interaction between AI integration and computer self-efficacy did not significantly predict trust in automated systems. This result suggests that overall trust in computer usage might not be enough to influence trust in highly advanced AI-based systems, in particular, when there is system use standardization or system use is compulsory.

On the whole, the research comes to a conclusion that the integration of AI into MIS is a key factor in the enhanced quality of the decisions, and trust and personal self-efficacy are supportive yet non-central factors in that case. The results add to the existing body of knowledge in the field of AI adoption by emphasizing that technical integration and organizational systems are crucial determinants of the role of individual psychological factors in decisions made in the sphere of the public sector.

### 5.3 Research Limitations

Although this research has its contributions, it also has a number of limitations, which have to be admitted. To start with, the cross-sectional type of research does not provide the possibility to make conclusions about causality. Despite the statistical relationships that were established, it is not possible to establish the temporal direction of effects conclusively. Longitudinal designs would have a more powerful effect on the evidence of how AI integration affects trust and decision quality in the long run.

Second, the case study was based on self-reports, which can be affected by the common method bias and social desirability factors. The perception of AI integration, trust, and quality of decision made by respondents may not be a genuine assessment of the system's performance or an objective decision made by the system. This might be improved by using objective indicators or multi-source data in the future in order to improve the validity.

Third, the sample was selected in terms of organizations in the public sector in Islamabad and Rawalpindi, which might limit the generalizability to other locations, as well as the private-sector organizations, or countries with other technological infrastructures and governance systems. A difference in culture, institutions, and policy can have a role in the adoption and impact of AI.

Lastly, the research had a few variables of study. The other crucial aspects were omitted, like transparency of the system, quality of training, organizational culture, and governance with ethical practices, which can be significant in determining the trust and decision outcome.

## 5.4 Recommendations

Upon the empirical evidence gathered as a result of the research, a number of practically oriented, policy-oriented, and research-based recommendations are made to facilitate the successful implementation of the AI integration in the sphere of Management Information Systems and to increase the quality of the decisions taken in the organizations of the public sector.

### 5.4.1 Organizational and Managerial Recommendations

To begin with, the systematic and strategic implementation of AI technologies in the Management Information Systems of the public-sector organizations should be given top priority by them. Instead of introducing AI tools in a haphazard and even trial-and-error way, organizations are encouraged to pursue a cohesive strategy that matches AI capacity with the strategic, tactical, and operational-level decision-making requirements. This will see the incorporation of predictive analytics, advanced dashboards, automated reporting, and data-driven forecasting applications, which directly feed into the managerial decision-making processes.

Second, organizations need to pay attention to enhancing the quality of data, the interoperability of the system, and the readiness of infrastructure because the efficiency of the AI-based MIS is highly predetermined by the access to high-quality, timely, and complete data. Data governance frameworks, data format standardization, and secure data-sharing mechanisms should be implemented to make sure that AI systems are making accurate outputs that can be trusted to make a decision.

Third, even though the trust of automated systems was not the strategic mediator between AI integration and the quality of the decisions, the organizational attempts to strengthen the transparency and explainability of AI systems are essential. Managers would need to make sure that AI-generated recommendations are readable and that there is a clear explanation of the underlying assumptions, data sources, and limitations. It can minimize uncertainty, eliminate the need to rely on AI outputs too much or abuse it, and encourage responsible decision making, especially when the stakes are high in the public-sector.

### 5.4.2 Human Resource and Training Recommendations

Fourth, training programs ought to go beyond the level of being computer literate and orient towards AI-specific capability. The lack of significance of computer self-efficacy as a moderator implies that the overall confidence in use of computer is not enough to build trust towards advanced AI systems. Consequently, companies ought to develop specific capacity-building initiatives that would increase the knowledge of employees in terms of AI concepts, decision support planning on an algorithm basis, data interpretation, and ethical considerations of automated systems.

Fifth, they need to implement continuous professional development programs that will make employees more critical of AI productions instead of taking them uncritically. The training must be focused on human-AI collaboration so that decision-makers may integrate domain knowledge and AI-finished information. Such a balanced solution can lead to the maximum quality of decisions and reduce the risks of automation bias.

Sixth, cross-functional teams should be promoted involving IT professionals, data scientists, and end-users in organizations. This kind of cooperation can contribute to the fact that AI systems are planned and introduced in the way that mirror the real decision-making needs and customer demands, thus increasing the usefulness and acceptance of the systems.

### 5.4.3 Policy and Governance Recommendations

Seventh, political leaders and administrators ought to come up with clear regulatory and ethical standards that would govern the application of AI in MIS in the public sector. Such guidelines are obliged to cover the concerns of data privacy, accountability of algorithms, mitigation of bias, and access to automated decision-making. The adoption of AI systems can be supported by institutional confidence using formal governance mechanisms.

Eighth, the performance assessment and accountability systems must be revised to indicate the application of AI-enhanced decision-making. Managers would be advised to apply AI tools in a responsible manner and still reserve the last decision-making power so that the responsibility of human decision-makers does not turn over to technology.

### 5.4.4 Recommendations for Future Research

Ninth, longitudinal research designs should be used in future research to investigate the dynamics of AI integration, reliance on automated systems, and quality of decisions made. This would enable the researchers to capture the effect of learning, maturity of the system, and shift in perceptions towards the user which is not possible in cross-sectional studies.

Tenth, the future research should include the moderator of AI-specific self-efficacy or digital intelligence instead of general computer self-efficacy. These constructs can more adequately describe the abilities of individuals to engage with complex AI-based systems and describe differences in trust and system utilization.

Lastly, a recommendation should be made to carry out comparative studies that may involve both public and private sectors and study that may be conducted in various cultural and institutional settings to maximize on the generalizability. It might also be possible to include other variables like organizational culture, transparency of the system, support of leadership as well as ethical climate to have a more detailed picture of how the integration of AI can impact decision-making outcomes.

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# Scales

### AI Integration into MIS Scale (AIMIS-10)

This questionnaire measures the level of Artificial Intelligence (AI) integration into Management Information Systems (MIS), specifically designed for public-sector organizations in Pakistan. Please indicate your agreement with each statement using the following scale:

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

1. AI-based analytics are incorporated into our MIS to support routine decision-making.
2. Our MIS uses predictive models (e.g., forecasting, trend analysis) to improve planning and performance.
3. AI algorithms are integrated into MIS dashboards to automatically generate insights for managers.
4. The MIS in my organization includes automated decision-support features powered by AI.
5. AI tools are linked with MIS databases to analyze large volumes of public-sector data.
6. AI features (e.g., alerts, pattern detection) help identify issues or anomalies within the MIS.
7. MIS reports in my organization are enhanced through AI-driven data interpretation.
8. AI chatbots or automated assistants are integrated into MIS for operational queries and support.
9. Our MIS uses machine learning models to suggest or recommend actions to decision-makers.
10. AI technologies are well-integrated into MIS workflows, contributing to efficient public-sector service delivery.

**Decision-Making Quality Scale (DMS-10)**

Instructions:

Please rate each statement on a 5-point scale:

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Items:

1. Decisions I make using MIS/AI outputs are well-founded and lead to correct outcomes.
2. I usually achieve the intended objectives when I follow recommendations from our MIS/AI systems.
3. The information from MIS/AI helps me choose options that solve the problem effectively.
4. When using MIS/AI, I can make decisions within required timeframes.
5. MIS/AI outputs help me reduce the time needed to reach a final decision.
6. I feel confident about the decisions I make using MIS/AI information.
7. I rarely experience doubt after making decisions based on MIS/AI. (Reverse-coded)
8. I am decisive when acting on recommendations provided by MIS/AI systems.
9. My MIS/AI-based decisions take into account relevant stakeholder needs and constraints.
10. Decisions made using MIS/AI are communicated clearly and accepted by colleagues/stakeholders.

**Brief Inventory of Technology Self-Efficacy Short Form (BITS-SF)**

**Items**

For each of the following statements, the respondent is asked whether they believe they can perform that activity. The response format is **Yes / No** (not Likert).

1. I can use a computer's task manager.
2. I can restart a computer.
3. I can use programming languages to write code.
4. I can browse the Internet.
5. I can set up a router.
6. I can overclock a computer.

**Scoring Criteria and Procedure**

Each "Yes" response is scored as **1**, each "No" as **0**.

**Total score** = sum of all Yes responses → **minimum 0, maximum 6**.

**Interpretation of total scores**:

- 0 → Negligible computer self-efficacy (CSE)
- 1–2 → Novice level CSE
- 3 → Novice-to-Advanced CSE
- 4 → Advanced CSE
- 5 → Advanced-to-Expert CSE
- 6 → Expert CSE

Only the **total score** should be used as the measure of computer self-efficacy when using BITS-SF

## Trust in Automated Systems (TIAS) – Items & Details

**Origin & Purpose**

The scale was developed in 2000 by Jian, Bisantz & Drury to measure a person's subjective trust in automated or AI-driven systems / machines. It is widely used in automation / human–computer interaction research.

**Scale Format & Response Format**

**Number of items:** 12

**Response scale:** 7-point Likert scale: 1 = Not at all to 7 = Extremely (or equivalent, depending on adaptation). The scale covers both **trust** (positive) and **distrust** (negative) items. Participants rate how much they agree with each statement about "the AI system they are evaluating.

**Items**

1 The AI system is deceptive. *(reverse-scored)*

2 The AI system behaves in an underhanded manner. *(reverse-scored)*

3 I am suspicious of the AI system's intent, action, or output. *(reverse-scored)*

4 I am wary of the AI system. *(reverse-scored)*

5 The AI system's actions will have a harmful or injurious outcome. *(reverse-scored)*

6 I am confident in the AI system.

7 The AI system provides security.

8 The AI system has integrity.

9 The AI system is dependable.

10 The AI system is reliable.

11 I can trust the AI system.

12 I am familiar with the AI system.

- Items 1–5 represent **distrust** (negative). Items 6–12 represent **trust** (positive).
- In many studies, negative (distrust) items are reverse-scored and then combined with positive items to yield an overall trust score.

**Scoring Procedure**

1. Respondents rate each item on a 7-point scale (1 = Not at all … 7 = Extremely).

2. For items 1–5 (distrust items), scores are **reverse-coded**. That is, e.g., if a respondent chooses 7 on “The system is deceptive,” after reverse scoring it becomes 1.
3. Compute the **sum or average** of all 12 items to produce a composite “Trust in Automated Systems” score (some studies use the mean).
4. A higher overall score indicates **higher trust**.

## Informed Consent

You are invited to participate in a research study examining how **AI integration into Management Information Systems (MIS)** influences **decision-making quality** in the public sector, and how **trust in AI** may mediate this relationship, with **computer self-efficacy** acting as a moderator. Participation involves completing a short questionnaire that will take about 10–15 minutes. Your involvement is completely voluntary, and you may withdraw at any time without penalty. All responses will remain confidential, and no identifying information will be collected. There are no known risks associated with participation, and your responses will contribute to a better understanding of AI-supported decision-making in public organizations. By proceeding with the survey, you indicate that you have read this information and willingly consent to participate.

**Demographic Variables**

1. **Age**
   (Categorical or continuous; age influences technology adoption, trust in AI, and decision-making behavior.)
2. **Gender**
   (Useful for understanding variation in technology perceptions and self-efficacy.)
3. **Education Level**
   (Higher education often correlates with AI awareness, MIS usage, and decision-making competence.)
4. **Designation**
   (Assistant Director, Manager, IT staff, Administrative staff, etc. Helps identify differences in system use.)
5. **Department**
   (Finance, HR, IT, Operations, Administration, AI exposure varies across departments.)
6. **Years of Experience**
   (Experience influences familiarity, comfort, and trust in digital systems.)