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Role of Artificial Intelligence in Construction Industry of Pakistan

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Abstract— *The quick development of technology, with a focus on Artificial Intelligence (AI), has resulted in significant changes on a worldwide level. The integration of AI across the full project lifecycle is still in its infancy in the construction sector. To improve the performance of the construction business, rising digital advances like AI must be embraced, although construction companies in developing countries have lagged slightly in doing so. The world has seen tremendous changes as a result of the quick development of technology, particularly Artificial Intelligence (AI). However, the adoption of new digital advances like AI in the construction industry, particularly in developing nations like Pakistan, is still in its early phases. The built sector's construction organizations in these nations have been sluggish to understand the value of integrating AI. This study tries to pinpoint the key organizational elements required to encourage AI adoption in Pakistani construction businesses. This research tries to identify the vital organizational elements that are crucial for promoting the use of AI in the construction industry. To do this, a quantitative survey strategy was used to collect data, using a snowball sampling technique to select industry experts as respondents. These professionals were polled on the issues surrounding the use of AI in building. In order to determine the crucial organizational elements that can accelerate the adoption of AI within the sector, an exploratory factor analysis (EFA) was subsequently conducted on the acquired data. Data from participants will be gathered using a quantitative survey methodology for the project. The relationship between these constructs will also be established via confirmatory factor analysis. The study suggests a number of elements, broken down into four categories, that influence organizational AI adoption: a creative organizational culture, competence-based training, group decision-making, and strategic analysis. Additionally, a confirmatory factor analysis (CFA) was used to provide more light on the connections between the discovered constructs. This study offers a thorough list of characteristics that are essential for promoting corporate AI adoption. Notably, this research presents organizational factors related to AI adoption in the construction and related industries using both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), a method that has not been frequently used in the articles identified in the systematic literature review (SLR). Prior studies have addressed organizational factors related to AI adoption in the construction and related industries. A deeper understanding of the underlying elements and how they interact within the context of AI adoption in the construction industry is made possible by the use of CFA, which increases the construct measurement's accuracy. The ultimate goal of this research is to improve knowledge of the underlying elements of these constructs and how they relate to AI application in Pakistan's construction sector. The study aims to add to knowledge and awareness of the potential of AI in Pakistan's construction business by putting light on these organizational aspects.*

Keywords*— *Artificial Intelligence, AI in Construction Industry, Pakistan Construction Industry, Organizational Factors.

I. BACKGROUND

Numerous productivity issues in the building industry in developing nations pose serious barriers to their advancement. These problems, which are mostly brought on by the repetitive and labor-intensive nature of construction operations, include a lack of competent workers, low productivity levels, excessive material wastage, and unsafe working conditions (Pradhananga et al., 2021). In addition to these issues, Windapo and Cattell (2013) have noted a number of other difficulties that the building sector in developing countries faces. These difficulties include, among other things, the effects of globalization and technology, as well as limitations in the public sector's capability and a lack of the requisite skills. These limitations as a whole reduce the effectiveness of construction procedures and limit the expansion of the construction industry in these nations (Ivanov and Aldeen, 2018).

The importance of the construction sector in the growth of economies around the world must be acknowledged (Isa et al., 2013). Governments can use this sector to accelerate a country's economic development and eventually move from being a developing country to a developed country (Yap et al., 2019). The construction sector must adopt efficient and effective solutions that encourage infrastructure development, boost the local economy, lower prices, and improve construction efficiency in order to bring about this change (Pheng and Hou, 2019). In order to garner more interest from legislators, researchers, and business professionals, the industry must prioritize raising service quality and level of knowledge (Alinaitwe and Ayesiga, 2013). Throughout the lifecycle of a construction project, this procedure entails combining crucial data from several disciplines (Yousif et al., 2021).

In the modern environment, it is becoming increasingly necessary to create construction systems and processes that combine technological advancements that can improve the construction process (Diniz Fonseca, 2021). According to Sun et al. (2020), technical development is the primary force behind the construction industry's continual transformation. As a result, there is increasing pressure on the industry to change from a sector that has been sluggish to adopt new technologies to one that does so wholeheartedly (El Jazzar et al., 2021).

Olanipekun and Sutrisna (2021) point out that industry experts, businesses, and governmental organizations from all over the world are progressively expressing a preference for digital technologies in building. One such technology that stands out and has several benefits for the construction sector is artificial intelligence (AI). These benefits include site planning, clear communication, visualization, logistics, and management of health and safety (Swallow and Zulu, 2019). But it's important to realize that the construction sector has lagged behind in adopting technology to fully address its problems (Nadhim et al., 2016; Delgado et al., 2019).

The majority of current technologies in the construction sector often concentrate on particular activities. For remote safety checks in construction projects, for instance, drones and UAVs have proven to be useful and efficient (Nnaji et al., 2019). The layer-by-layer deposition of materials like metals or polymers is made possible by 3D concrete printing technology (Adaloudis and Bonnin Roca, 2021). Building information modeling (BIM) is frequently utilized for a number of tasks, including as design development, 3D modeling, simulation, risk analysis, and environmental analysis (Shehzad et al., 2021). These technologies do in fact only partially address the issues facing the sector, but when combined with AI, they can provide more complete answers. Conventional design, manufacturing, and building techniques have been transformed by artificial intelligence (Manzoor et al., 2021). AI helps on-site processes in construction, such as automated bricklaying and welding, while also giving operators signals to reduce risks (Chakkravarthy, 2019).

The effects of AI go beyond conventional building techniques. By identifying and deducing specified concepts from architectural patterns, it can automatically enrich models (Sacks et al., 2020). Additionally, economics, geopolitics, sociology, the environment, demographics, and security are all impacted by AI (Yeh and Chen, 2018). Natural language processing, speech recognition, and machine learning are only a few of the quick computing tasks that AI is capable of (Sohn and Kwon, 2020). In addition to supporting site supervision, automatic detection, and intelligent maintenance, these functions allow AI to cluster construction schedules, transform text to speech in building amounts software, and cluster construction schedules (Hong et al., 2021; Olanrewaju et al., 2020; Xu et al., 2021).

The construction sector has a lot of room for intelligence and digitization thanks to artificial intelligence (AI), which is considered the oldest branch of computer science (Holzinger et al., 2019). It efficiently bridges the gap between the physical and digital realms in a variety of industries, offering the potential of significant automation, improved performance, and better reliability (Manzoor et al., 2021). The establishment of standard AI adoption infrastructures is a challenge for construction firms, despite the obvious benefits of AI adoption (Mahroof, 2019). The market value of AI technology may also cause hesitation among stakeholders in the building sector (Merschbrock and Munkvold, 2015). By easing data interchange, AI applications can significantly improve the development of the construction industry (Lekan et al., 2018).

In order to increase performance and efficiency in the built environment of developing nations, especially, it is urgent to embrace digital technologies (Windapo, 2021). The optimal and productive performance of the built environment is required for economic growth, which strongly depends on infrastructure development (Li et al., 2019). Operations and supply chain management research has centered on AI (Dubey et al., 2019). However, a lack of resources and capabilities limits the ability of many organizations, including those in the construction sector (Girginkaya Akdag and Maqsood, 2019). This constraint makes it difficult to respond to client demands and adjust to market fluctuations, both of which are essential for the successful deployment of AI (Paul et al., 2020).

The productivity of the construction sector depends on integrating applicable AI technology seamlessly and reforming organizations to increase productivity and efficiency (Lakhwani et al., 2020). Long-term sustainability in the construction market and industry depends on learning and innovation (Miranda et al., 2016). Mergers and acquisitions, structural and cultural changes, and procedural adjustments are only a few of the changes that affect companies in the construction sector (Sarala et al., 2019; Boadu et al., 2020). Incorporating technical infrastructure, human resource skills, and organizational commitment to change, organizational adoption is crucial (Saghafian et al., 2021). It's crucial to understand that, when considering technical considerations, organizational perspectives shouldn't be disregarded or dismissed (Metcalf and Benn, 2012). Organizational adoption of AI is a dynamic process that is driven by both internal and external factors. These factors have an impact on the organization's ability to embrace technology and, as a result, the adoption's results (Ren, 2019).

Additionally, the scale of construction companies varies, comprising both major corporations and SMEs. This variability may result in differences in how adoptions are handled. Therefore, a comprehensive approach is needed to solve these issues. The deployment of AI in the construction sector has been studied previously from a variety of perspectives. For instance, Mohamed et al. (2021) investigated the use of AI in the Malaysian construction industry, concentrating on enhancing project quality while reducing project duration, cost, and complexity.

Some of the statistics of construction industry are shown below for understanding the construction market in Pakistan.

Fig.1.1: Projected Growth

(Source: Board of Investment: https://invest.gov.pk/housing-and-construction)

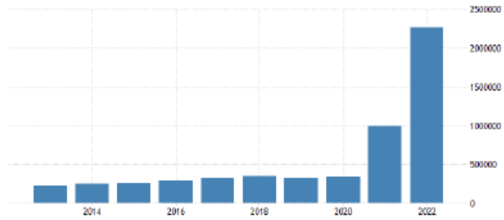

Fig.1.2: Pakistan's GDP from Construction

(Source: State Bank of Pakistan: https://tradingeconomics.com/pakistan/gdp-from-construction)

Problem Statement

The adoption of AI and related technologies has not been the exclusive focus of previous research on the construction sector, nor have these studies examined the connections between organizational elements that affect AI adoption. There hasn't been any actual research done on the use of AI in Pakistan's construction sector up until this point. As a result, it is still unclear what factors affect the adoption of AI in Pakistani construction enterprises. The study issue that examines the organizational variables of AI adoption in Pakistan's construction industry is still unclear as a result of this knowledge gap.

Research Objectives

This study's main goal is to pinpoint the organizational characteristics that are essential to encouraging AI adoption in the construction industry. These driving variables are proposed in the study, which divides them into four categories: creative organizational culture, competency-based growth, group decision-making, and strategic analysis. By doing this, it hopes to advance knowledge of the underlying causes that affect how these elements interact with the adoption of AI in Pakistan's construction sector.

Results of this research will pinpoint the key elements that encourage AI adoption in the construction sector, offering a useful knowledge base for successfully putting AI techniques into practice. Additionally, academics will use the empirical data acquired to help them create viable roadmaps for the adoption of AI in the construction sector, not just in Pakistan but also in other developing nations. This study will shed light on how the implementation of AI in construction companies might result in more effective and efficient operations by outlining a clear research design.

Research Significance

The research significance/question i.e. "What are the organizational factors of AI adoption in Pakistan's construction industry?" has been developed to fill this knowledge gap and provide light on this crucial field of study. The significance of this study question is to give Pakistani construction companies useful advice on how to integrate AI. This study also tries to discover the many AI-related constructs and then investigate the connections between these constructs. By providing a more thorough understanding of the organizational aspects associated to AI adoption in Pakistan's construction industry and how they are interconnected, this research seeks to fill these gaps and contribute to the literature on AI adoption.

II. LITERATURE REVIEW

- Artificial Intelligence (AI) Definition and Scope

A number of definitions of artificial intelligence (AI) have been offered by academics, all of which emphasize this technology's ability to process data, extrapolate knowledge from the past, and deal with uncertainty in the future. The simulation of cognitive functions similar to those of humans, albeit in a more visible and computational way, is how AI is frequently defined (Trocin et al., 2021). With the ultimate objective of enabling computers to think and act in ways that approximate human cognition, AI has been extensively defined in recent years as a field devoted to the study and design of intelligent agents (Smith, 2016; Shneiderman, 2020). According to Shi et al. (2020), the main goal of AI is to deal with problems that are difficult to formalize but that are relatively simple for people to solve using their natural intuition.

The introduction of big data analytics and the quick development of AI have created new opportunities for the use of various data sources, enabling data-driven decision-making and improving operational efficiency in a variety of fields. Organizations have greatly improved their management practices thanks to IT-enabled data collecting and analysis capabilities (Cho and Wang, 2021).

Organizational operations have been changed by this nexus of AI and data analytics, which has given businesses the means to harness the power of data and provide useful insights. By helping firms to extract important insights from huge amounts of information as well as analyze it, these technologies enable more strategic and informed decision-making. As a result, AI is now a crucial part of contemporary organizational strategy, promoting efficiency, competitiveness, and innovation in a wide range of industries (Addison et al., 2019; Bao et al., 2021).

Additionally, enterprises now have new chances to streamline their operations, improve customer experiences, and gain a competitive edge because to the synergy between AI and data analytics. Organizations are able to anticipate trends, spot patterns, and make in-the-moment adjustments thanks to the use of AI for predictive analytics and machine learning (Li and Zhang 2019; Kim et al. 2020). This improves operational outcomes and boosts customer satisfaction.

In short, AI and data analytics work together as a potent toolkit that enables businesses to fully utilize the potential of their data repositories. In a business environment that is becoming more data-driven and dynamic, this transformational capability not only improves decision-making but also fosters agility, innovation, and adaptability (Nguyen et al., 2021; Pan and Zhang, 2019).

Additionally, the importance of AI goes beyond just data processing; it also includes speech synthesis, image recognition, and natural language comprehension, all of which have numerous applications in industries like healthcare, banking, and customer service. With the help of these AI-driven skills, businesses can automate processes, enhance customer relations, and offer more specialized and effective services (Chen et al., 2021; Schuster et al., 2020).

The meaning and significance of AI have changed throughout time, with more recent interpretations highlighting its ability to mimic cognitive functions that are similar to those of humans and its crucial role in data-driven decision-making. The combination of AI and data analytics has ushered in a new era of efficiency and creativity, allowing businesses to use data for operational improvements and competitive advantage across a variety of industries. The way that businesses negotiate the complexity of the modern business landscape is changing as a result of the dynamic interaction between AI and data analytics.

- AI in Construction Organizations

The field of artificial intelligence (AI) is quickly developing and changing how businesses run and handle their activities. Due to its capacity to use tools like machine learning (ML) to steadily improve performance, AI has gained substantial notoriety in recent years (Dhanabalan and Sathish, 2018). Dhamija and Bag (2020) contend that AI holds the key to enacting significant operational changes inside current organizational frameworks. Arrotéia et al. (2021) say that AI has developed into a crucial tool for managing organizations and construction projects. In comparison to conventional procedures, it provides a comprehensive model that takes into account all facets, disciplines, and systems within a facility, permitting more precise and effective stakeholder collaboration.

The ability of AI to carry out jobs that previously required human cognitive talents is becoming more widely accepted by organizations. In terms of application range, adoption rates, processing speed, and capacity, AI systems continue to advance quickly (Haefner et al., 2021). Through the growth of technical and social skills, this evolution has given the construction industry a variety of capacities, ultimately improving project outcomes (Sima et al., 2020). These capabilities are the result of investments made by firms in AI, which cover communication, staffing, training, and other human resource areas (Ahuja et al., 2018).

According to Ghosh et al. (2018), machines are getting better at handling non-routine jobs. Organizations undergo a huge transition termed as "digital transformation" as AI and digital technologies continue to converge (Wu et al., 2021). AI is becoming a topic of great interest in industrial business practices and strategic information research.

It is important to remember that AI does not take the place of human intelligence; rather, it enhances it by making the best choices at the appropriate times. As shown by several research, there are a number of elements that affect the adoption of AI within enterprises. Knowledge and competency, as well as information processing management, were highlighted by Ghobakhloo and Ching (2019) as crucial elements in the implementation of organizational AI.

Employees must be knowledgeable and skilled in areas like information and digital technology (IDT), cybernetics, and data analytics because AI is associated with automation, the development of interconnected networks of intelligent machines and materials, and the integration of the real and virtual worlds. This suggests that for people to remain productive in AI-driven environments, their skills must constantly advance. AI plays a crucial role in the construction industry by improving information processing capabilities to handle the growing volume of data. As a result, businesses with greater information processing needs are more likely to use AI (Turner et al., 2020).

Performance, cost, governmental guidelines, and expertise are further elements that affect the adoption of AI (Turner et al., 2020). With less risk than is typically involved with building projects, AI can revolutionize part production, enable cost-effective construction techniques, and ultimately reduce construction costs as a whole. Additionally, the adoption of AI is significantly influenced by productivity, governmental laws, and business size (Likewsie, Mabad et al., 2021). Government laws and regulations can help or hurt the adoption of AI by the construction industry since they frequently influence how decisions are made about adopting new technologies (Likewsie, Mabad et al., 2021).

Additionally, key aspects that affect AI adoption inside enterprises include organizational preparation, top management support, decision-making support, cost considerations, skill development, and attitudes toward innovation (Jöhnk et al., 2020). The possibility of successful AI adoption is increased by organizational preparation, which is also necessary to maximize the business value of AI. A crucial element is top management support, which includes the readiness of senior leadership to launch AI activities from the top down and show support for bottom-up initiatives. Due to the various organizational needs connected with AI implementation, this support is essential. The decision to embrace AI by a company frequently depends on the approval of top management. Top management support is evidently demonstrated by the incorporation of AI adoption into organizational strategy and the development of AI knowledge and awareness (Jöhnk et al., 2020).

Also influencing AI adoption include time savings, cost savings, competitive pressures, and cooperation prospects (Garca de Soto et al., 2019). These incentives encourage firms to adopt AI, especially in the construction sector where there is a need to decrease lead times, improve quality, and lower costs by more effectively fusing design and construction processes.

Other important elements that affect AI adoption include risk assessment, adherence to standards, and decision-making assistance (McAleenan, 2020). For system designers and developers to manage the fast changing technical landscape, governmental entities, industry associations, and individual businesses frequently adopt rules and standards. These guidelines aid in ensuring that technical innovations adhere to moral and philosophical principles. The adoption of AI is also heavily influenced by factors such as costs, workplace cultures, relationships among employees, and attitudes toward innovation (Chatterjee et al., 2020). AI systems urge businesses to reorient their attention away from conventional cost-cutting and profit-boosting tactics. AI technology becomes essential because to the enormous amount of data that must be managed and assessed cost-effectively. Users—often employees within organizations—are more willing to accept AI technologies if they believe they would benefit their productivity. This welcoming mindset toward innovation motivates firms to adopt AI (Chatterjee et al., 2020).

Artificial intelligence (AI) has been increasingly used in construction projects in recent years, indicating the technology's enormous potential to boost efficiency and productivity in the sector. By performing an extensive analysis of papers on AI in construction, this paper seeks to offer an up-to-date viewpoint on the topic by contrasting its findings with those of past reviews (Sofie Bang, 2022).

A complex interaction of elements covering technological, organizational, and cultural dimensions affects the adoption of AI within enterprises. Organizations must carefully take into account these elements as AI develops in order to fully realize its promise, improve operational effectiveness, and maintain competitiveness in a constantly shifting business environment.

III. RESEARCH METHODOLOGY

To successfully accomplish its goals, this study used a variety of research methods. A thorough examination of the available literature was combined with a quantitative survey as the methodology of choice. This research strategy was chosen because, as highlighted by Apuke (2017), it is consistent with the study's objective nature, which aims to substantiate facts, discover patterns, examine links among statistically quantifiable variables, and analyze them using proper statistical procedures. The choice to use a quantitative research approach was purposeful since it makes it easier to develop quantitative assessment indicators, which Basias and Pollalis (2018) highlight as being a key component of the study. With the use of this method, essential factors may be measured and quantified, allowing for a more organized and quantitative interpretation of the research data.

The questionnaire methodology was selected as the main data gathering strategy for the survey component. There were various strong reasons why this decision was made. First, using questionnaires ensures that information is gathered quickly and effectively. They also offer a broad geographic coverage, allowing responders from various places to be included. Additionally, surveys give respondents the chance to thoroughly evaluate and confirm data, encouraging accuracy in their responses, an important component of rigorous research technique (Jones et al., 2013).

Additionally, questionnaires are a resource-efficient way to gather data because they just need a small amount of time, money, and supplies. They are a sensible option for research projects because of their affordability (Datti et al., 2019). In addition, questionnaire administration and setup are both fairly simple, which contributes to their widespread use in research projects.

The study procedure itself was structured and involved several steps, as shown in Figure 3.1. The first step included doing a thorough literature analysis to lay the groundwork for existing knowledge and pinpoint the primary research interests within the field of study. Then, a questionnaire survey was carried out to obtain first-hand information from respondents.

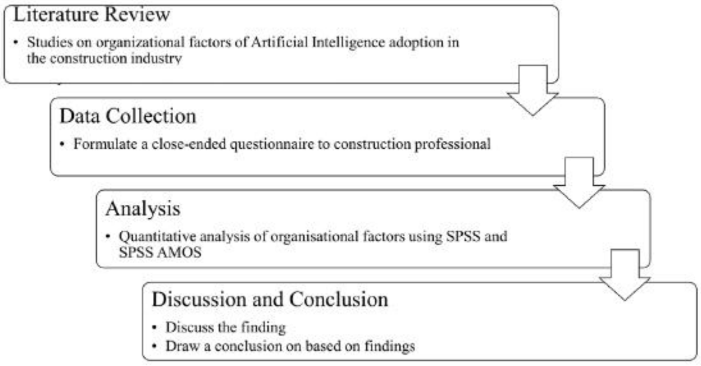

Fig.3.1: Research Process

The study involved data analysis using the Statistical Package for the Social Sciences (SPSS) after data collection. This analysis used a variety of statistical methods, such as exploratory factor analysis (EFA) and the determination of mean item scores (MIS). These analytical techniques played a crucial role in analyzing the connections between constructs and uncovering underlying patterns in the data. The study also used SPSS AMOS for additional analysis, particularly to evaluate the constructions that surfaced during the investigation. This rigorous method to data analysis sought to draw insightful inferences and conclusions from the research results, thereby advancing our comprehension of the subject matter of the study.

Literature Review

The first step in this research project was to perform a thorough literature analysis with the aim of identifying and clarifying the key elements that affect the organizational aspects of AI in the construction sector. A thorough systematic literature review (SLR) was conducted in order to accomplish this. The SLR methodology was chosen on purpose since it has clear benefits for research protocol transparency and accuracy. Systematic literature reviews are recognized for their exacting and systematic way of surveying the amount of knowledge already in existence. With a precise emphasis on the topic of interest—in this example, the organizational aspects relevant to AI within the construction sector, as explained by Tian et al. (2018)—researchers using this approach meticulously search, evaluate, and synthesize pertinent papers within a defined field.

The SLR's systematic design makes sure that the research process follows clear, well-defined protocols, boosting the accuracy and legitimacy of the results. It entails a thorough search for and examination of studies that are pertinent to the study issue, facilitating a thorough grasp of the material. The SLR methodology was used in this study to ensure that all important aspects influencing AI inside construction firms were discovered and thoroughly assessed. The study meticulously acquired and analyzed a wide range of significant scholarly publications. The systematic review approach is particularly useful since it enables researchers to combine findings and derive insightful conclusions by offering a structured and organized overview of the body of literature.

This study's comprehensive literature review, which was carried out in the first stage, was carefully chosen for its transparency and methodological rigor. By methodically assessing and combining significant papers in this area, our approach allows for a full examination of the organizational issues related to AI in the construction sector.

Review Protocol

The creation of an organized review methodology is a requirement of the first stage of a systematic literature review (SLR). This important step includes a number of vital components intended to successfully direct the research process. Let's explore these elements in greater detail.

Research Questions: The design of precise and thorough research questions forms the basis of the review protocol. These inquiries define the parameters and goals of the study and serve as the basis for the entire SLR. The review will be focused on the most important features of the selected issue thanks to carefully constructed research questions.

Systematic Search strategy: A strategic strategy is essential when conducting a comprehensive search for pertinent material. Researchers use the right databases, keywords, and search strings to carefully prepare and carry out their search operations. This methodical technique makes sure that no important studies are missed.

Inclusion Criteria: For the review process to be successful, inclusion criteria must be clearly defined. These requirements specify the precise qualities research must have in order to be taken into consideration for review. These criteria may include elements like publication date, study technique, and relevance to the research topics in the context of AI organizational variables in the construction industry.

Process for Quality Appraisal: The protocol includes a rigorous process for quality appraisal. Researchers evaluate the trustworthiness and methodological soundness of the chosen studies. The most reliable and trustworthy sources of information are determined with the aid of this careful review.

Data Extraction and Synthesis: A well-organized plan is created for data extraction and synthesis. To do this, pertinent data from the chosen studies must be methodically extracted, organized, and synthesized to yield actionable conclusions.

Transparency in methodology: Transparency in methodology is essential. Researchers follow a set of precise instructions to make sure the review process is open, repeatable, and understandable to other academics. The review's findings are more credible and reliable because of this transparency.

Course Direction: The review protocol serves as a compass, directing the researcher through every step of the SLR procedure. It makes sure the investigation stays on course and adheres to its set goals.

Methodological Advancement: A well-structured review methodology can be a useful tool for future research projects in addition to directing the current investigation. For academics interested in researching related subjects, it may serve as a source of methodological advice and a reference.

A systematic literature review is established on the framework of a review protocol. It offers the organization and direction required to manage the challenges of the research process. Additionally, it improves methodological transparency, guaranteeing that the study is carried out precisely and rigorously. An SLR can produce complete and trustworthy insights into the chosen research domain by following these careful processes.

Based on the above discussion, the research question proposed for the research is "What are the organizational factors of AI adoption in the construction industry?".

A number of rigorous procedures were carried out to make sure the study subject was thoroughly explored. According to de Carvalho et al. (2017), the established research protocol included crucial elements such as information about the research question itself, the choice of sample articles, the creation of a search strategy, and the identification of pertinent keywords to precisely define the study's scope. According to de Melo et al. (2020), the procedure also included a careful assessment of the inclusion and exclusion criteria.

Inclusion and Exclusion Criteria

The criteria for inclusion in this review were specifically chosen to guarantee the selection of empirical studies that were directly relevant to the study's focus, which is the organizational factors impacting the adoption of AI in the construction industry and adjacent sectors. The following essential components were included in these criteria:

Relevance: The studies that were chosen have to be directly related to the research topic, which is the analysis of organizational variables influencing the adoption of AI technology. This criterion made sure that the studies that were picked had a direct bearing on the area of research that was being done.

Publication Language and Period: Only research published in English was taken into consideration for inclusion in order to ensure consistency and comprehensibility. Recent advancements in the use of AI were taken into account when choosing this particular historical period, which was in line with the research's current setting.

Publication Type: Only articles published in respectable journals and peer-reviewed conferences were included in the review in order to uphold the scientific rigor and credibility of the chosen sources. This criterion was designed to make sure that the studies that were picked had undergone thorough examination and inspection by subject-matter experts.

The thorough use of these inclusion criteria was essential in ensuring that the research review included empirical studies that met strict criteria for academic rigor and quality as well as being directly relevant to the research topic. According to Wager and Wiffen (2011), the review attempted to reduce the possibility of retrieving inaccurate or biased data by adhering to these criteria.

Additionally, precise exclusion criteria were put in place to increase the validity of the results and preserve the review process's integrity. These exclusion criteria were created to weed out studies that did not follow the review's specified guidelines. Excluded research were often deemed unsuitable for inclusion in the review because they did not fall within the purview of the selected industry, did not conform to the established time span, language, or publication type.

The review aimed to make sure that the chosen studies not only met strict requirements for scholarly quality but also were highly relevant and wisely applied inclusion and exclusion criteria. This careful strategy attempted to improve the review's findings' validity and reliability, ultimately resulting in a more solid and reliable study output.

Study Search

Researcher used a wide range of search phrases to cast a wide net in our hunt for related papers. The use of artificial intelligence (AI) within the construction sector, particularly in the context of the Fourth Industrial Revolution (4IR) and digitalization, is the focus of our research. These search phrases covered important parts of this research. We carefully used Boolean operators like AND and OR, as well as specific database operators, to narrow searches and obtain the most pertinent literature. By employing special characters like truncation (*) or (?) throughout the search process, these operators allowed researchers to describe logical linkages between our search phrases and accommodate for variances in terminology. Following the advice given by Madigan et al. (2014), the researcher made sure that our search turned up a wealth of pertinent literature by using this thorough approach. This wide-ranging collection of sources had a crucial role in guiding our research and analysis, making the study more substantial and perceptive.

Selecting Studies (inclusion Based on Pre-Defined criteria)

Several electronic databases, including ASCE Journals, Emerald Insight, Elsevier ScienceDirect, Engineering Village, Google Scholar, ICE virtual library, IOPscience, IEEE Xplore, Elsevier Scopus, SpringerLink, and Taylor & Francis, were searched to find the research' sources.

Data Extraction from Studies

Following the article extraction procedure, we conducted a screening of essential data, eliminating the need for a thorough reading of all the papers. Then, following Samsudin et al.'s (2022) technique, we used ATLAS.ti to systematically arrange and perform a thematic analysis of the chosen papers. These conclusions were used as the basis for creating a questionnaire that was distributed to Pakistani construction industry professionals in order to collect first-hand information. The exhaustive literature review yielded the following table 3.1, which lists seventeen organizational aspects of AI adoption in the construction industry.

Table 3.1: Organizational Factors

S/No	Organizational Factors
1	Information Processing Management
2	Knowledge and competency
3	Improve performance
4	Cost to organization
5	Organizational Culture
6	Government pressure
7	Collaboration
8	Firm size
9	Organizational readiness
10	Top Management support

11	Attitude to innovation
12	Time-saving
13	Competitive pressure
14	Risk involved in using AI technologies
15	Standards
16	Reputation
17	Decision making support
18	Work culture
19	Workplace relationship of staff

Data Collection

A thorough questionnaire was designed by the researcher to elicit opinions from building industry experts around the nation. When created and used appropriately, questionnaires have developed into crucial tools for eliciting statements from certain individuals, groups, or even entire populations (Roopa and Rani, 2012). This methodology is extremely useful for gathering data from a wide range of responders, who are often referred to as subjects.

Researcher used a Google Forms-made online questionnaire to speed up data collecting. The questionnaire was carefully designed to cover a variety of topics, including insights into organizational factors driving the adoption of AI and demographic data about respondents. Using a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree), with a midpoint of 3 (neutral), respondents were asked to submit their opinion. The choice of this measure was based on how well it captured the attitudes and thoughts of the respondents (Munyasya and Chileshe, 2018).

Table 3.2: Likert Scale

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

I used a combination of judgmental and snowball sampling techniques in my effort to connect with a wide group of construction professionals. This strategy targeted people in professional networks, especially business professionals. In addition, the researcher used email and social messaging services like LinkedIn to get in touch with possible volunteers who lived in the study's geographic area. These social media sites act as gathering places for people of all backgrounds, helping to build a vibrant social network of industry experts (Kapoor et al., 2017).

Because of its non-random selection method, it's important to keep in mind that the judgmental sampling technique, while useful for focusing in on people with certain viewpoints, does not allow generalization to the entire population (Etikan and Bala, 2017). In contrast, snowball sampling, which is likewise non-random, involves employing a small initial group of respondents to entice the involvement of further cases and thereby increase the sample size (Taherdoost, 2016). Through this small group, the first contacts within the scope of the study were made; these contacts then helped with the recruitment of more participants. By asking each respondent to identify more possible participants, this technique helps create networks and boost participation numbers. Because it was not practical to recruit respondents from the demographic indicated through LinkedIn, I chose these non-probability sampling techniques (Lehdonvirta et al., 2020). Instead, I drew on respondents' desire to take part in the study and their knowledge of construction methods (Darko and Chan, 2018).

According to de Winter et al. (2009) and Pearson and Mundform (2010)'s recommendations, my goal was to collect data from 150 individuals overall for this study, which is more than the minimum required. After the data collection period, 169 completed questionnaires were finally received and examined. A wide range of occupations in the construction industry were represented by these respondents, including architects, quantity surveyors, civil engineers, construction managers, and construction project managers.

Data Analysis, Results and Interpretation

A thorough examination of the data was performed using both descriptive and inferential statistical methods. The determination of means and the extraction of major components were two important outputs produced by this analytical method. The Statistical Package for the Social Sciences (SPSS) and SPSS AMOS (Analysis of Moment Structures) are two potent software programs that were used to help these investigations. The data needed to be summarized and presented in a comprehensible fashion, and descriptive statistics were essential for this. These statistics were useful in clarifying the dataset's central tendencies, dispersions, and distributions. In contrast, inferential statistics went further and allowed for the investigation of connections, distinctions, and patterns that might not have been immediately evident in the raw data. Drawing conclusions and generating judgments about the larger population from whom the data were taken were made easier thanks to this stage of the analysis. A key measure of the data's average value—the calculation of means—was offered, illuminating the usual or representative value within distinct variables. This was very helpful for comprehending the dataset's general properties.

A more sophisticated analytical method that intended to minimize the dimensionality of the data while keeping its important information was the extraction of principle components. The dataset's underlying structures or patterns were identified using principal component analysis (PCA), which may have revealed hidden variables or associations that were not immediately apparent using more conventional techniques.

The research team used SPSS and SPSS AMOS, two specialized software tools, to conduct these analyses efficiently and thoroughly. A well-known statistical software program called SPSS offered a complete set of tools for carrying out a variety of statistical studies, including inferential tests and descriptive statistics. On the other hand, the team was able to examine more intricate correlations and structural patterns within the data thanks to SPSS AMOS, a program that specializes in the study of structural equation models and moment structures.

The means were calculated and principle components were extracted as part of the data analysis procedure, which included both descriptive and inferential statistics. These studies were carried out utilizing the powerful features of SPSS and SPSS AMOS, ensuring a rigorous and thorough examination of the features and underlying structures of the dataset.

Mean Item Score

The main participant data set underwent thorough analysis, with the Mean Item Score (MIS) serving as the primary analytical tool. According to Sarhan et al.'s 2018 study, MIS acts as a quantitative representation of the degree of consensus or agreement among respondents regarding the major organizational elements driving the adoption of artificial intelligence (AI) in Pakistan's construction industry.

A descriptive statistics technique was used to give a more thorough assessment of the study's participants and the current status of AI applications within businesses in the construction sector. As recommended by Nasila and Cloete in 2018, this involves the development of numerous statistical indicators to capture central patterns and data dispersion.

The average values in the dataset were calculated using the arithmetic mean, a measure of central tendency. This statistic reflected the typical response or rating participants gave to several aspects influencing AI adoption. Additionally, as stated by Evans et al. in their 2021 research, the standard deviation (SD), a quantitative measure of the amount that individual responses deviate from the mean, played a critical role in assessing the variability within the dataset. A low SD suggested that the replies were closely packed around the mean, indicating a high degree of participant agreement. In contrast, a high SD meant that the respondents' responses covered a larger range of values, suggesting a more varied variety of thoughts and attitudes.

As suggested by Ejohwomu et al. in their 2017 study, the MIS was once more used to create a ranking of the factors driving AI adoption from highest to lowest based on their mean scores. The Likert scale, a widely used instrument for evaluating and comparing respondent preferences or attitudes, was used to determine this rating. The study was able to determine the relative importance of several organizational components in the context of AI adoption within the Pakistani construction industry by using this scale.

The Mean Item Score (MIS), which measures participant agreement, was used in the analysis of the original data set. In order to give a thorough overview of respondent characteristics and the state of AI applications in construction sector businesses, descriptive statistics were also used. The arithmetic mean and standard deviation were computed as part of this, with the latter serving as a gauge of data dispersion. The Likert scale and MIS made it easier to rank organizational components according to their mean scores, illuminating their relative significance in influencing AI adoption.

Exploratory Factor Analysis

According to Ngowtanasuwan in 2019, exploratory factor analysis (EFA) is a computational tool used to determine the underlying structure that controls a dataset's various variables. By selecting and keeping only the most important descriptive characteristics, this method is essential for streamlining complex data and improving the dataset's interpretability. It is crucial to carry out a number of preliminary evaluations to make sure the data is appropriate for factor analysis before beginning the EFA procedure. For this, the Bartlett's sphericity test and the Kaiser-Meyer-Olkin (KMO) test are used. According to Zeray et al. in 2021, the KMO test analyzes if the sample size is enough in relation to the number of variables. A KMO score above 0.45 is generally regarded as appropriate. In contrast, Bartlett's test of sphericity evaluates whether the correlations between variables are sufficiently different from random chance, and according to Ul Hadia et al.'s findings in 2016, a significant result (p 0.05) is typically required for factor analysis to be deemed appropriate.

As stated by Effendi et al. in 2020, after performing these first checks, the following phase entails investigating the total variance explained, which is an essential step in the item extraction procedure intended to reduce the number of variables for a more manageable study. According to Matsunaga's 2010 recommendation, objects with eigenvalues greater than 1.0 are divided into multiple components and used to identify discrete components within the dataset.

Additionally, the rotated variable matrix is carefully examined to narrow down the list of objects to be studied in more detail. As indicated by Maskey et al. in 2018, only objects with factor loadings greater than 0.5 are kept in this step. A threshold of 0.5 ensures that only the most significant relationships are taken into account. Factor loadings show the strength of the relationship between variables and factors.

In short, a computational method used to reveal the underlying structure of multivariate datasets is called exploratory factor analysis (EFA). It is preceded by a number of evaluations, such as the KMO and Bartlett's tests, to check the applicability of the data. The extraction of significant components from the dataset is aided by the total variance explained and eigenvalues, and the factor loadings direct the choice of variables for further analysis, all of which together help to reveal the underlying structure of the data and improve its interpretability.

Confirmatory Factor Analysis

As described by Maleti et al. in 2013, Confirmatory Factor Analysis (CFA) was used in this study as a powerful statistical tool to verify convergent validity, examine the suitability of the measurement model, and identify links between distinct dimensions. In order to achieve this, the study used the results of a previous Exploratory Factor Analysis (EFA) as the basis for carrying out the CFA. According to Kim et al.'s findings in 2015, the CFA was conducted to validate the latent variables and measurement variables, and the analysis was carried out using the SPSS AMOS statistical tool.

For accurate results in CFA, ensuring a proper sample size is crucial, with various researchers providing conflicting recommendations. According to Zahoor et al. (2017), a sample size of 200 is adequate to ensure the accuracy of the findings when using confirmatory factor analysis. On the other hand, Kyriazos (2018) contends that a sample size greater than 100 is required to produce reliable results for a CFA model with 3–4 indications per component.

A crucial phase in CFA is the evaluation of the model fit, which entails taking into account a variety of fit indices that each offer insight into various facets of model fit. As a result, the study published a thorough set of goodness-of-fit indexes, based on prior research and suggestions. These indices were chosen in accordance with the recommendations made by Chan et al. in 2017. As a result, a variety of fit indices were used, as shown in Table 4.1, that were comparable to those used by Chan et al. in 2014, Molwus et al. in 2017, Tanko et al. in 2017, Zahoor et al. in 2017, and Puiu in 2020.

Confirmatory factor analysis (CFA) was used in this study as a useful statistical tool to evaluate convergent validity, gauge the suitability of the measurement model, and identify links between constructs. The CFA was performed using the statistical tool SPSS AMOS, with the EFA results serving as the foundation. The study followed recommended sample size guidelines and incorporated Kyriazos' and Zahoor et al.'s and researchers' insights. Additionally, a number of fit indices were used to thoroughly assess the model fit, as shown in

Table 4.1, in accordance with suggestions from the literature.

Table 4.1: Organization Model Fit Indices.

Fit Indices	Recommended Measure
CMIN/df = discrepancy divided by degree of freedom (Chi-square value. If significant, the model can be considered unsatisfactory).	Good < 3, acceptable < 5
Root mean sq. error of approx. (RMSEA)	0.05 (very good) - 0.1 (threshold)
Root mean sq. residual (RMR)	0 – 1 (smaller values = better fit)
Goodness-of-fit index (GFI)	0 (no fit) - 1 (perfect fit)
Comparative fit index (CFI)	
Incremental fit index (IFI)	
Tucker-Lewis index (TLI)	

Validity and Reliability

The consistency and coherence of results acquired with a measurement tool or instrument are referred to as reliability, which is a basic notion in research technique. According to Creswell and Guetterman in 2019, the objective is that scores should remain constant and show little variance when an instrument is administered repeatedly at various times. In essence, it makes sure that the instrument's data are trustworthy and suitable for analysis. The Likert scale proved to be a reliable assessment tool in the context of this investigation. The little variety found in the replies to certain scale items made this clear. In other words, participants' answers showed a high level of consistency and stability when they responded to the identical questions on various occasions.

On the other hand, validity is concerned with whether the results of an instrument are significant and can help the researcher come to reliable conclusions regarding the sample population under study. Internal validity, a subset of validity, evaluates how closely the measurements obtained in the research setting match the data that the measuring tool was intended to record. As indicated by Mohajan in 2017, researchers frequently utilize Cronbach's alpha (α), a commonly used indicator of internal consistency, to assess the measurement instrument's internal reliability. Cronbach's alpha measures how closely related a group of elements in an instrument are, effectively evaluating how well they capture the same underlying construct. According to Sileyew in 2019, this coefficient is commonly understood as the average of all feasible split-half coefficients, leading to a comprehensive evaluation of internal consistency.

Strong internal consistency and high reliability of the measurement equipment are indicated by a high Cronbach's alpha coefficient, which is near to 1. This suggests that the instrument consistently measures the same underlying construct via its items. However, as evidenced by the results of Nair et al. in 2019, it is generally agreed that a minimum Cronbach's alpha coefficient of 0.70 is required to deem the construct internally consistent and highly dependable. Validity ensures that measurement instrument scores are relevant and enable reasonable inferences about the research population, whereas reliability assures the stability and consistency of measurement instrument scores over time. The study used Cronbach's alpha as a gauge of internal consistency and reliability, with a recommended cutoff point of 0.70 to denote a high degree of the instrument's internal consistency and reliability.

Ethical Considerations

When conducting research, it is essential to thoroughly examine ethical issues in addition to choosing the right study approach and processes. According to Fleming and Zegwaard in 2018, ethical considerations are the cornerstone of good human-participant research, and they demand careful consideration and commitment. This study was guided by a number of important ethical principles, including beneficence, autonomy, and fairness. According to the beneficence principle, it is the responsibility of researchers to preserve research participants' welfare and keep them free from exploitation of any kind. As emphasized by Barrow et al. in 2021, this means making sure that any information supplied by participants during their involvement in the study remains private and secure. The study also highlighted the potential advantages of AI in construction, such as lowering human mistake rates and boosting project productivity, which would be consistent with the principle of beneficence.

Another crucial ethical premise that guided this research was autonomy, often known as respect for persons, as promoted by Singh and Hylton in 2015. It demands that researchers uphold participants' autonomy by giving them the choice of participating or not in the study. This concept emphasizes the significance of getting participants' informed agreement and guaranteeing that their involvement is completely voluntary. As discussed by Soboan et al. in 2018, researchers have an ethical responsibility to avoid any injury or discomfort to research volunteers, whether accidental or purposeful, and to reduce any potential hazards connected with the study. This entails taking precautions to safeguard the physical and mental health of participants during the course of the study.

Finally, choosing research participants fairly is required by the justice principle. According to ydinait in 2018, this involves abstaining from all forms of prejudice and guaranteeing that participant populations are selected fairly and without pressure. Participants in this study came from both public and private companies in Pakistan and represented a varied range of construction professions, including project managers, quantity surveyors, architects, and civil engineers. By including individuals from different racial and cultural origins, emphasizing inclusivity, and avoiding any kind of bias or exclusion, the research embraced diversity.

The research process includes ethical concerns that take into account ideals like beneficence, autonomy, and fairness. This study made sure that the rights and well-being of research participants were upheld and respected, and that the research was carried out in a responsible and equitable manner by abiding by these ethical principles and getting ethical approval.

IV. RESULTS

- **Respondents Profile**

Table 4.2 contains a thorough overview of the 169 respondents' profiles, giving a complete picture of the study's participants. The profiles of the respondents' educational and professional backgrounds, occupations, organizational ties, and levels of experience can be thoroughly analyzed to provide important insights. First and foremost, the results make it clear that a sizeable percentage of the respondents, approximately 67.5% of the total, had a bachelor's or honors degree as their highest level of schooling. This demonstrates a solid basis in terms of academic qualifications and points to a well-educated responder pool. Furthermore, 16% of the participants had master's degrees, highlighting the sample's diversity in terms of educational background. When evaluating the respondents' distribution of professions, it was found that 48.5% of them identified as quantity surveyors. This demonstrates how common this career is among the participants. Civil engineers trailed closely behind with 24.9% of the responses, showing a significant representation of this occupational group in the research.

Table 4.2: Respondents' Profile

Profile	Description	Frequency	Percentage (%)
Qualification	Matric/Grade12	7	4.1
	National Diploma	19	11.2
	Bachelor's/Honors' Degree	114	67.5
	Master's Degree	27	16
	Doctorate	2	1.2
Profession	Architect	9	5.3
	Quantity Surveyors	82	48.5
	Civil Engineer	42	24.9
	Construction Manager	21	12.4
	Construction Project Manager	15	8.9
Organization	Public Client	22	13
	Private Client	41	24.3
	Contracting Organization	59	34.9
	Consulting Organization	47	27.8
Experience	1–5 years	103	60.9
	6–10 years	31	18.3
	11–15 years	13	7.7
	More than 20 years	8	4.7

The majority of participants, or 34.9%, were employed by contracting organizations in terms of organizational affiliation. This may indicate that a sizable percentage of respondents were actively employed in the construction sector in positions connected to project execution. Following closely after, 27.8% of the respondents worked for consulting firms, illustrative of the range of positions and responsibilities present in the industry. Examining the respondents' degrees of professional experience, the data shows that a significant 60.9% had between 1 and 5 years of experience. This indicates that a sizeable portion of the study's professionals are in their early careers. Furthermore, 18.3% of the participants said that they had between six and ten years of experience, which added to the range of experience levels across the respondent pool.

The 169 respondents' profiles, which are shown in Table 4.2, provide important details about the make-up of the study's participants. The information highlights the prevalence of bachelor's/honors and master's degrees among the respondents, the dominance of the professions of quantity surveyors and civil engineers, organizational affiliations, and professional experience distribution. This thorough profiling prepares the way for a complex and perceptive examination of the research findings in light of the backgrounds and features of the participants.

- **Descriptive Results**

Our detailed descriptive analysis of the replies from the survey participants regarding the organizational elements influencing the adoption of AI within Pakistan's construction industry is presented in Table 4.3 below. This analysis clarifies the numerous criteria listed in the questionnaire and provides a thorough breakdown of their Mean Item Scores (MIS), illuminating the perceived importance of these aspects in relation to the adoption of AI. Overall, it is interesting that every organizational element studied in this study received MIS ratings more than 3.50, suggesting the participants' perceptions of its relevance and significance. This indicates that the respondents generally agreed on the significance of these variables for the adoption of AI technology within Pakistan's construction industry.

Table 4.3: MIS analysis of organizational factors of AI adoption in Pakistan's construction industry.

	Mean	Std. Deviation	Inter-Quartile Rang
Top management Skills	4.02	0.92	4.00
Decision Making support	3.99	0.81	4.00
Cost to Organization	3.98	0.99	4.00
Improved performance	3.95	0.87	4.00
attitude to innovation	3.88	0.97	4.00
Organization's work culture	3.85	0.92	4.00
Collaboration	3.83	0.90	4.00
Organizational readiness	3.83	0.91	4.00
Time-saving	3.83	1.07	4.00
Knowledge and Competency	3.82	1.03	4.00
Standards	3.75	0.95	4.00
Information Processing Management	3.69	0.99	4.00
Governmental pressure	3.64	1.01	4.00
The workplace relationship among staff	3.62	1.01	4.00
Risks involved in using innovative technologies	3.61	1.10	4.00
The reputation of the organization	3.60	1.08	4.00
Firm size	3.57	1.11	4.00

"Top management skills" had the highest MIS score of the evaluated organizational characteristics, achieving an excellent mean score of 4.02. This shows that study participants gave this factor the greatest weight when discussing the adoption of AI. The importance of leadership skills in directing and managing the integration of AI technology is highlighted by the identification of top management abilities as a crucial component. Following closely behind, "decision-making support" received a MIS of 3.09, indicating that respondents found it to be highly relevant. This aspect emphasizes how crucial it is to have sufficient support systems and procedures in place to encourage well-informed decisions on the deployment of AI.

The organizational component "cost to the organization" also displayed a noticeably high MIS of 3.98, highlighting the importance of this element in the landscape of AI adoption. It's clear that participants used the financial ramifications and cost-effectiveness of AI integration as a major deciding factor. The characteristics that received the lowest MIS scores, however, included "risks involved in using innovative technologies" (MIS = 3.61), "reputation of the organization" (MIS = 3.60), and "firm size" (MIS = 3.57). Despite having lower scores, these factors are nonetheless important in the adoption of AI, albeit with a little lower perceived importance than the elements with higher MIS values.

The participant perspectives on the numerous organizational elements impacting the adoption of AI in Pakistan's construction industry are accurately portrayed in the descriptive analysis that is offered. According to the MIS scores, these elements are deemed to be important, with "top management skills," "decision-making support," and "cost to the organization" standing out as particularly significant factors. However, despite receiving a somewhat lower rating, "risks associated with utilizing innovative technologies," "organizational reputation," and "firm size" are still important when discussing the adoption of AI. This report offers a useful starting point for future investigation and discussion of the elements influencing AI adoption in Pakistan's construction industry.

- **Exploratory Factor Analysis**

A crucial statistic in data analysis, the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy, registered an amazing value of 0.895 in this case. The dataset is suitable for factor analysis if this value is greater than the generally recognized cutoff of 0.70. As a result, their aggregation into related sets for the extraction of factors in the exploratory factor analysis (EFA) is justified because the variables under investigation demonstrate acceptable multi-collinearity structures. Additionally, Bartlett's Test of Sphericity produced a significant result at p 0.001, reiterating that the information about the organizational elements influencing AI adoption is definitely appropriate for factor analysis, as shown in Table 4.4.

Table 4.4: KMO and Bartlett's Test

Kaiser-Meyer-Olkin measure of Sampling Adequacy		0.895
Bartlett's Test of Sphericity	Approx. Chi-Square	1298.571
	Df	136
	Sig	0.000

According to Table 4.4, the EFA procedure entailed extracting principal components while being constrained by the requirement of beginning eigenvalues greater than 1. Four components in total were found to be the ideal number of factors for this particular EFA, and they accounted for an astonishing 62.43% of the explained variance, according to the research. According to how they were distributed, the first component was responsible for 41.747% of the variance, the second explained 7.76%, the third explained 6.852%, and the fourth component was responsible for 6.070% of the variance overall. The data's underlying structure is revealed by these findings, which are depicted in Table 4.5 as discrete variables that capture the essence of the organizational determinants driving AI adoption.

Component Initial Eigenvalues Rotation Sums of Squared Loadings

Table 4.5: Total Variance

	Total	% Of variance	Cumulative %	Total	% Of variance	Cumu
1	7.097	41.747	41.747	3.609	21.228	21.
2	1.319	7.760	49.506	2.924	17.200	38.
3	1.165	6.852	56.359	2.315	13.617	52.
4	1.032	6.070	62.429	1.765	10.383	62.

The organizational factors discovered for AI adoption by Pakistan's construction professionals are grouped into four main component groups in Table 4.6, which provides an in-depth summary of the EFA results. The first component covers the work culture of the company and discusses how employees interact with one another at work, the cost to the company, organizational readiness, standards, and the company's attitude toward innovation. Competitive pressure, information processing management, business size, expertise, competency, and government pressure are some of the characteristics of component 2. Top management abilities, decision-making support, and teamwork shed light on component three. Improved performance, hazards related to adopting AI technologies, and time-saving considerations are all part of component four. A thorough analysis of the dataset's underlying components was supplied by the EFA method, which also gave a sophisticated knowledge of the organizational aspects driving the adoption of AI in the context of Pakistan's construction industry. The study's analytical depth and interpretative value are increased by the extraction of four major components and their corresponding explanations in Table 4.6. This deepens our understanding of these factors and their interactions.

Table 4.6: Rotated Component Matrix and Cronbach Alpha

		Factor loading	Cronba alpha
Component No.1	Organization's work culture	0.781	0.835
	The workplace relationship among staff	0.704	
	Cost to organization	0.697	
	Organizational Readiness	0.681	
	Standards	0.515	
	attitude to innovation	0.488	
Component No.2	Competitive pressure	0.726	0.807
	Information Processing Management	0.709	
	Firm size	0.627	
	Knowledge and competency	0.510	
	Government pressure	0.543	
Component No.3	Top management skills	0.763	0.770
	Decision making support	0.762	
	Collaboration	0.710	
Component No.4	Improved performance	0.67	0.667
	Risks involved in using AI technologies	0.629	
	Time-saving	0.623	

- **Confirmatory Factor Analysis**

The generated output from the confirmatory factor analysis produced scores for the fit indices that were moderately favorable, showing that the measurement model demonstrates a respectable fit to the data. The effectiveness of the model was assessed using a number of important fit indicators. First off, the Chi-square value, which was 311.47 and had a p-value below 0.001, indicated a result that was statistically significant. It is important to recognize that Chi-square is sensitive to sample size and that other indices are often more useful for evaluating model fit than Chi-square.

The degree of freedom, which is calculated as 3.42 (CMIN/df), is the ratio of the Chi-square value to the degrees of freedom. This ratio is within an acceptable range even though it is somewhat higher than the optimum cutoff point of 3, suggesting that the model may still be regarded as having a decent fit.

The Root Mean Square Residual (RMR), with a value of 0.072, and the Root Mean Square Error of Approximation (RMSEA), which both had values of 0.12 and 0.12 respectively, are acceptable. These indices increase confidence in the model's overall fit to the data by indicating that it cannot be rejected with a high degree of certainty.

The Goodness-of-Fit Index (GFI), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Incremental Fit Index (IFI) were also assessed as important fit indices. Although particular values for the GFI and CFI were not given, they are crucial metrics for evaluating model fit. The TLI (0.781) and IFI (0.838) stated values show that the fit between the measurement model and the data can be judged to be most definitely acceptable, adding to the confidence in the model's suitability.

The findings of the confirmatory factor analysis are summarized in Table 4.7, which shows that the measurement model reasonably aligns with the observed data, as shown by a variety of fit indices. All of these findings support the model's suitability for describing the relationships between variables.

Table 4.7: Fit Indices

Fit indices	Recommended Measure	
Chi-square	Tabled x^2 value	
Significance		<0.(
value Degrees of Freedom		9:
CMIN/df	Good <3, acceptable <5	
Root mean sq. error of approx. (RMSEA)	0.05 (very good)-0.1 (threshold)	
Root mean sq. residual (RMR)	0–1 (smaller values = better fit)	
Goodness-of-fit index (GFI)	0 (no fit)-1 (perfect fit)	
Comparative fit index (CFI)	0 (no fit)-1 (perfect fit)	
Incremental fit index (IFI)	0 (no fit)-1 (perfect fit)	
Tucker-Lewis index (TLI)	0 (no fit)-1 (perfect fit)	

Additionally, Table 4.8 shows that the performed model supports the four discovered components' favorable and statistically significant influence on organizational AI adoption. By offering empirical proof of the significance of these characteristics in promoting AI adoption within the corporate setting, this conclusion significantly contributes to the study's goals.

Table 4.8: Regression Coefficients

Factor	Path-coefficient	Standard error	t-value	Significance (p)
Innovative Organizational Culture	0.239	0.069	3.448	0.001
Competence Based Development	0.304	0.082	3.713	0.001
Collaborative decision making	0.161	0.056	2.897	0.004
Strategic Analysis	0.291	0.095	3.07	0.002

- **Descriptive Results**

From the descriptive statistics, top management skills (x̄ = 4.02, SD = 0.92, IQR = 4.00), decision making support (x̄ = 3.99, SD = 0.81, IQR = 4.00) and cost to organization (x̄ = 3.98, SD = 0.99, IQR = 4.00) are the top three highest-ranked in the descriptive analysis ranked highest in the descriptive analysis. However, risks involved in using innovative technologies (x̄ = 3.61, SD = 1.10, IQR = 4.00), the reputation of the organization (x̄ = 3.60, SD = 1.08, IQR = 4.00) and firm size (x̄ = 3.57, SD = 1.11, IQR = 4.00) were the least ranked variables.

These results are in line with the 2020 study by Jöhnk et al., which underlines the critical importance of senior management support for the implementation of AI programs within enterprises. Managers who develop the appropriate skills and knowledge are essential in fostering an environment that supports the adoption and use of cutting-edge technologies. These managers are specifically entrusted with learning about industry best practices and studying how their rivals have successfully embraced innovation. According to Yusof et al. in 2014, competitive intelligence becomes a useful tool for managers in making decisions regarding the viability and risk of various technologies, which eventually affect the organization's industry reputation and profitability.

This supports McAleenan's research findings from 2020 regarding the significance of decision-making support. As stated by Sepasgozar et al. in 2018, organizations put a lot of work into risk management techniques because they understand that bad judgments and the subsequent requirement to replace subpar technology can cause major delays and large additional expenditures.

Furthermore, the results concur with the viewpoints offered by Pan and Pan in 2020 and Chatterjee et al. in 2020, particularly with regard to the cost element. However, it's important to note that these findings differ from those of Olawumi and Chan in 2020, mainly because establishing an AI infrastructure in a company comes with substantial initial expenses. Bello et al. in 2020 challenge this view by arguing that AI technologies give construction enterprises access to cutting-edge computing infrastructure and apps, each of which could demand a large financial investment. However, over time, this investment leads to decreased overall project delivery costs, providing construction businesses with a clear competitive and operational advantage. It's interesting to note that the conclusions on the dangers of adopting AI differ from those of McAleenan's research from 2020. Diffusion of technology within the construction sector tends to lessen the perceived risks attached to its deployment in the environment. According to Darko et al. in 2017, this in turn affects industrial practitioners' interest in implementing these technologies.

The results also call into question the viewpoint presented by Garca de Soto et al. in 2019 about the maintenance of corporate reputation. In reality, keeping one's reputation and image is very important to construction companies. According to van Heerden et al. in 2018, the implementation of AI not only improves record-keeping but also aids in preventing bad publicity that can sour ties with stakeholders.

The findings in regards to firm size are consistent with Pan & Pan's perspective from 2020. This suggests that when it comes to the creation and adoption of innovation, both small and large firms have distinct benefits. Due to the fact that innovation orientation is influenced by factors other than organizational size, as emphasized by Kamal et al. in 2016, firm size is not a strong predictor of AI-related activity.

An exploratory factor analysis was carried out to fully comprehend the organizational elements impacting the adoption of AI within the Pakistani construction industry. Four clusters were formed by grouping different variables, and confirmatory factor analysis was then applied to these clusters to reveal the links between the constructs. These organizational characteristics as determined by the exploratory factor analysis are illustrated in Figure 4.1.

Fig.4.1: Diagrammatic Representation of the Organizational Factors

- **Component 1 - Innovative Organizational Culture**

Six sub-components make up this particular component, each of which adds to our understanding of the organizational aspects driving the adoption of AI.

Work Culture in the Organization (0.781): This sub-component indicates the overall culture of the organization and how open-minded it is to adopting AI. It implies that the company culture has a significant impact on whether or not AI technologies are integrated successfully.

Interpersonal interactions in the Workplace (0.704): This sub-component emphasizes the significance of interpersonal interactions in the workplace. It implies that friendly working environments can help create a setting that is more favorable for the successful adoption of AI.

Cost to the Organization (0.697): This sub-component places special emphasis on the financial costs of adopting AI. It emphasizes how the decision-making process for integrating AI technology is heavily influenced by cost considerations within the enterprise.

Adaptability of the organization (0.681): This sub-component explores how ready the organization is to incorporate AI. It includes elements like the organization's capacity to negotiate the complexities of AI technology as well as the availability of resources, both financial and human.

Standards (0.515): Organizational standards are crucial for directing the deployment of AI. This sub-component indicates that the incorporation of AI technologies can be sped up by clearly established standards.

Organizational Attitude Toward Innovation (0.488): The organization's attitude toward innovation plays a significant role in determining the trajectory of its adoption of AI. This sub-component emphasizes that adoption of AI is facilitated by a favorable attitude toward innovation.

According to the table, this group of sub-components accounts for a significant 41.747% of the total variance. A path coefficient of 0.239 and a p-value of 0.001 highlight the importance of this component. These results, however, run counter to the viewpoint offered by Olawumi and Chan in 2020. The findings imply that when there is strong support from the corporate culture, innovation can flourish within businesses. Routines, practices, conventions, and organizational cultures that encourage innovation help organizations make the change from traditional processes to AI technology. It suggests that before successfully integrating AI into their building operations, businesses may need to go through cultural reforms, which is consistent with the findings of Yap and Toh from 2019.

However, it's critical to recognize that many businesses have financial limitations that prevent them from experimenting with innovation. According to Mark et al. in 2021, this restriction inhibits their capacity to learn from and improve upon successful ideas, which ultimately limits their adaptability and attitude toward innovation. According to Enegbuma et al. in 2015, AI delivers a new tool and procedure that has the potential to significantly alter people, processes, communication, and the ineluctable workplace culture.

The perspectives of Chatterjee et al. in 2020, Olawumi and Chan in 2020, and Pan and Pan in 2020 are all supported by these findings. Together, they argue that effective leadership in businesses should take a comprehensive stance in order to influence workers' attitudes and intents about the adoption of new systems.

Another sub-component, organizational preparation, emphasizes the necessity for both financial and human resources in the context of AI adoption in the construction industry. Additionally, it shows that organizational readiness, as proposed by Salazar and Russi-Vigoya in 2021, offers insights into AI maturity assessments, comprising elements like performance, dependability, durability, and operational experience in the predicted environment.

The results also highlight the crucial role that stakeholders in the construction industry play in promoting innovation uptake. As stressed by Yuan et al. in 2021, stakeholders create regulations and standards, provide guidance, and offer assistance, considerably lowering the risks related to the use of AI technologies.

This component and its subcomponents give insight on many organizational elements, including cultural, relational, financial, and preparedness issues, that influence AI adoption. As shown graphically in Figure 4.1, these insights offer a thorough comprehension of the complex processes at play within enterprises as they negotiate the deployment of AI technologies.

- **Component 2 - Competence-Based Development**

Five different sub-components within this component have been found; each one adds to our understanding of the factors affecting the adoption of AI.

Competitive Pressure (0.726): This sub-component emphasizes the significance of industry-level competition as a catalyst for the uptake of AI. It emphasizes how businesses are under pressure to incorporate AI-based developments in order to stay competitive and gain an advantage in their particular industries.

Management of Information Processing (0.709): The management of information within organizations is covered in this sub-component. It means that efficient information management and processing techniques are necessary for the deployment of AI to be successful.

Firm Size (0.627): Within this cluster, firm size is a crucial sub-component. It implies that an organization's approach to adopting AI depends in part on its size. The adoption of AI is influenced by size-related aspects in both small and large enterprises.

Knowledge and Competency (0.510): This cluster's essential sub-components emphasize the value of human expertise and capacities in promoting the adoption of AI. This sub-component's important features are decision-making and competency-based development.

Government Pressure (0.543): This sub-component discusses how government pressures and policies may affect the adoption of AI in the construction sector. It means that policies or laws from the government may have an impact on the adoption landscape.

As seen in Table 4.3, this group of sub-components accounts for 7.760% of the overall variance. Significantly, with a p-value of 0.001 and a path coefficient of 0.304, this component is statistically significant. These results are consistent with the viewpoints offered in 2020 by Olawumi and Chan. They emphasize the crucial part that human knowledge capacities play in supplying the knowledge that businesses need to effectively adopt AI technologies. The integration of numerous knowledge domains and skills, necessary for making informed decisions in a variety of contexts, is a component of competency-based development. As suggested by Lantelme et al. in 2017, stakeholders can improve their competencies by dealing with a variety of difficult scenarios.

Organizations, especially those in the construction sector, embrace AI-based innovations to keep their competitive edge as a result of competitive pressure. The findings further support the fact that innovation and knowledge transfer speed are crucial for businesses in this industry, where the importance of innovation as a source of sustainable competitive advantage is becoming increasingly clear. According to Sergeeva and Duryan in 2021, project-based firms' use of AI is evidence that they have come to the conclusion that AI plays a crucial role in the creation of new knowledge and capacities.

According to Ghobakhloo and Ching in 2019, the findings highlight the significance of establishing information management capabilities as this is linked to better AI innovation dissemination across the construction industry. According to Alwan et al.'s 2017 discussion, AI provides construction organizations with optimization strategies and opportunities to use information management techniques and collaboration platforms, benefiting a variety of resource flows, including workforce, building information, equipment hire, and material procurement.

According to Mabad et al. in 2021, small construction enterprises in remote locations would have trouble getting access to the requisite knowledge to facilitate AI deployment. The use of AI may be constrained by a lack of broad government backing for infrastructure-building and construction AI initiatives. As Bolpagni and Bartoletti noted in 2021, this frequently leads to decision-makers giving attention to daily operations over the possible long-term advantages of AI.

This component and its sub-components provide valuable insights into the multifaceted factors influencing AI adoption, encompassing competitive dynamics, information management, organization size, knowledge and competency, and government policies. These insights contribute to a holistic understanding of the intricate interplay of influences within the context of AI adoption, as depicted in Figure 4.1.

- **Component 3 - Collaborative Decision Making**

Three different sub-components have been identified within this component, each of which adds to our understanding of the variables influencing the adoption of AI:

Superior management abilities (0.763): This sub-component emphasizes how important senior management capabilities are for promoting AI adoption within enterprises. It emphasizes the need of leadership in staff training, raising public awareness of AI, and successfully deploying cutting-edge technologies. Top management plays a crucial role in making decisions, reforming regulations, and assisting with training to enable AI integration.

Decision Making Support (0.762): This cluster's essential sub-component emphasizes the contribution of AI to helping enterprises make well-informed judgments. It suggests that using AI to help overcome obstacles, conflicts, and anomalies that arise during project execution will ultimately improve decision-making throughout the project's lifespan.

Collaboration (0.710): This crucial sub-component highlights the significance of organizational staff members cooperating to create AI-based systems. It underlines that the chance of adopting AI technology is increased by an organization's capacity for productive collaboration in the development of AI systems.

As seen in Table 4.3, this group of sub-components accounts for 6.852% of the overall variance. With a p-value of 0.004 and a path coefficient of 0.161, this component was not discovered to be statistically significant, which is important.

These results are consistent with the viewpoints offered by McAleenan, Olawumi, and Chan. AI-enabled digital technology, such as collaborative decision making, is characterized as an integrated process that functions in a shared and virtual environment and involves stakeholders from many domains. Stakeholders can evaluate, plan, and carry out projects at various phases of their life cycles using this collaborative approach. In this collaborative setting, effective information transfer is essential for lowering errors, controlling costs, and improving the caliber of communications across various stakeholders. According to Pidgeon and Dawood in 2021, using cutting-edge technologies and governance procedures is also made possible by it.

The results also highlight the significance of advanced management capabilities in the successful application of AI technology in the construction sector. Top management has a major role to play in educating and raising staff understanding of AI as well as weighing the advantages and disadvantages of implementing construction robots. There are several ways to help leadership, including assisting with decision-making, reorganizing procedures to incorporate novel ideas, and offering training support. The importance of AI in decision-making is stressed, especially in reaction to difficulties and anomalies found while carrying out a project. AI is equipped with tools for gathering and reusing knowledge, which can help with decision-making.

The importance of employee collaboration in creating AI-based systems is underlined as a key element in encouraging the adoption of AI technology. Collaboration and engagement between various stakeholders and specialists are crucial throughout the project life cycle in construction organizations that prioritize projects. However, as noted by Pan and Pan in 2020, reaching agreement on the implementation of innovations among various groups inside these organizations might be difficult.

This component and its supporting sub-components give light on the critical role top-level management abilities, AI-assisted decision-making, and successful collaboration play in the context of adopting AI. Even though this particular component was not statistically significant, these insights help to create a comprehensive picture of the numerous factors that drive adoption.

- **Component 4 - Strategic Analysis**

Three different sub-components have been identified within this component, each of which adds to our understanding of the variables driving the adoption of AI:

Improved Performance (0.67): The significance of AI technology in improving performance within enterprises is highlighted by this sub-component. In numerous facets of construction organizations and projects, it implies that AI tools help to increase prediction, modeling performance, and accuracy. Additionally, AI enables the development of digital procedures and service innovations, which in turn increase perceived fairness, lessen decision-making bias, offer open feedback, and promote better communication.

Risks Associated with AI Technology Use (0.629): This component's sub-component emphasizes the understanding of potential hazards related to implementing AI technologies. It indicates that businesses consider the benefits and drawbacks of adopting AI, understanding that while these technologies may have long-term advantages, they may also present difficulties and demand trade-offs—especially in Pakistan, where AI adoption is still in its infancy.

Time-Saving (0.623): The third sub-component, time-saving, emphasizes the efficiency improvements made achievable by AI technology. AI has the potential to automate processes and lessen human labor, which will help businesses by saving time.

According to Table 4.3, this group of sub-components accounts for 6.070% of the total variance. With a p-value of 0.002 and a path coefficient of 0.291, this component was not determined to be statistically significant, which is an important distinction to make.

These results are consistent with the viewpoints offered by Turner et al. and Mabad et al. An effective organizational strategy is established in large part through strategic analysis. In order to make educated decisions on potential strategies, it entails a thorough study of an organization's resources, capabilities, and external environment. Organizations must balance the advantages and disadvantages of adopting AI while understanding that, despite initial difficulties and sacrifices, there may be substantial long-term gains. A realistic assessment of the available possibilities should serve as the foundation for the sensible selection of solutions.

The results further highlight the importance of AI technology in raising organizational performance. Improved prediction and modeling capabilities provided by AI tools increase the accuracy of many building project components. AI also makes it easier to construct new digital procedures and services, which improves fairness, lessens decision-making bias, creates open feedback systems, and improves communication.

Additionally, the idea of communities of practice is presented, with the hypothesis that these groups could develop into risk-free, loosely coupled operating systems that support organizational learning and innovation. According to Sergeeva and Duryan, such communities can cross functional and project barriers, encouraging creativity and effective problem-solving.

This component and its sub-components shed light on the significance of enhanced performance via AI, the understanding of dangers connected with AI adoption, and the major time-saving advantages that AI technology can give. Despite the fact that this particular component was not statistically significant, it advances knowledge of the elements impacting AI adoption in the construction sector.

V. CONCLUSION, IMPLICATIONS, RECOMMENDATION AND FUTURE RESEARCH

Implications for Research

The adoption of AI and related technologies as well as the investigation of links among organizational factors are two crucial issues that the corpus of existing research on AI in the construction industry has largely ignored. This study fills in these gaps in the literature and greatly advances the use of AI. First off, by throwing light on the organizational elements involved in AI adoption within Pakistan's construction industry, this study contributes to the body of knowledge on AI adoption. It goes deeply into these complexities, offering a thorough and nuanced explanation of their impact on the uptake of AI technologies. Both academics and industry professionals can benefit from this improved understanding of organizational dynamics and how they affect the adoption of AI.

Additionally, this study takes things a step further by examining the connections between these organizational elements. It provides a comprehensive understanding of the AI adoption process by revealing the complicated relationships and correlations between various variables. Professionals in the construction sector can use this comprehensive viewpoint to help them make well-informed choices about how to incorporate AI technologies into their daily operations.

The development of a solid knowledge foundation on the adoption of AI is another benefit of this study. It not only pinpoints the key elements affecting AI adoption but also lays the foundation for useful suggestions meant to speed up the effective implementation of AI methods in the construction sector. These guidelines are helpful for business people that want to use AI to its full potential within their firms.

Additionally, the empirical data produced by this study is a useful tool for both scholars and decision-makers. It offers a concrete dataset that can assist in the creation of strategic road plans for Pakistan's building sector. Furthermore, other developing nations facing comparable opportunities and problems in adopting AI can gain from the conclusions drawn from this study.

This study makes a variety of contributions to the topic of AI adoption in the building sector. It not only identifies the organizational variables affecting adoption but also looks into how they interact. This information guides the creation of strategic roadmaps and serves as the basis for recommendations that are both practical and efficient for the companies in the construction sector.

Implications for Practice

Organizational management could be revolutionized by incorporating AI into a variety of corporate activities and services. Adopting AI technologies can result in significant cost savings while also improving the quality of the goods and services that organizations deliver. Organizations must constantly evaluate their productivity in the highly competitive environment of today, paying particular attention to the important aspects this study has identified. By doing this, they get a strategic edge that enables them to fully utilize the adoption of AI throughout numerous areas of their operations.

Setting and maintaining targets is one of the key areas where AI can have a transformative effect. Organizations can make data-driven decisions, spot performance trends, and modify their plans thanks to AI-driven analytics and predictive models. This data-centric strategy includes streamlining workflows, improving overall accountability within the company, and optimizing key business processes. Organizations can achieve new levels of performance and efficiency by utilizing AI.

Adoption of AI also considerably aids knowledge management techniques. Organizations may create strong institutional knowledge repositories by using AI-powered solutions that make it easier to store, share, and acquire knowledge. This information can be used to encourage creativity, problem-solving, and well-informed choices. A company's ability to profit from its intellectual assets is improved by the seamless integration of AI into knowledge management operations.

Organizational leadership can be crucial in promoting the use of AI. Management and leadership teams must grasp the strategic importance of AI technologies. Organizations can open up prospects for increasing production, improving efficiency, ensuring quality, and promoting teamwork by adopting AI. Adopting AI is not just a scientific undertaking; it is also a strategic necessity that can have long-term advantages.

Additionally, the implementation of AI can aid in resolving some of the industry's persistent problems. The industry has frequently struggled with problems linked to sustainability, safety, and effectiveness. These sectors could be improved by AI technology, which would eventually boost the industry's reputation. AI-driven solutions can improve safety procedures, streamline the building process, and promote sustainable practices, ultimately changing how people view the sector.

However, as businesses begin their adoption of AI journey, a number of challenges and ambiguities must be resolved. Significant obstacles include the lack of common frameworks for different AI technologies, the rising demand for AI solutions, and the requirement for stronger stakeholder participation and collaboration. In addition, it's important to properly negotiate contractual intricacies, legal issues, and regulatory compliance.

Government agencies and business organizations must take the initiative to make AI adoption in the construction sector easier. Organizations may be encouraged to use AI technologies via industry standards and governmental laws. Pilot projects and workshops can be useful tools for showcasing the real-world uses of AI, in line with the factors our study has highlighted.

Additionally, investing in the development of human capital is necessary to encourage the use of AI. Worker attitudes and behavioral intentions can be changed through the use of training programs and initiatives, which will develop a favorable attitude toward the use of AI in the construction sector. The workforce should be given the training that they need to effectively use AI through these initiatives.

Construction organizations, among others, have a transformative opportunity due to the use of AI. It has the ability to improve organizational management, spur efficiency, and boost the sector's perception as a whole. But for these advantages to materialize, there must be a determined effort on the part of the labor, industry associations, and governing agencies. Organizations can successfully implement AI and enjoy the benefits of a more technologically sophisticated future by tackling difficulties, raising awareness, and investing in human resources.

Conclusions

It's still unclear whether AI will be adopted in the construction sector, especially in organizations in underdeveloped nations. In many areas, the actual advantages of AI adoption have not yet been completely appreciated. This paper makes a substantial contribution to the body of academic work on the usage of AI in developing nations. It clarifies the key issues that Pakistan's construction sector must deal with as it tries to integrate AI technologies into its administrative structure. The complexity of AI adoption variables within the construction and associated industries in developing nations has been the subject of many prior studies, but this one stands out because it took a complete approach. It differs from earlier studies in that it uses both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to systematically measure and validate these important constructs.

This research's thorough literature evaluation and empirical inquiry into this knowledge gap resulted in the identification of distinguishing traits relating to AI adoption inside construction industry organizations in developing nations. The comprehensive literature evaluation revealed a wide range of factors influencing the adoption of AI, offering a solid framework for further investigation. The study then used a factor analysis to identify the underlying organizational elements that affect Pakistani construction industry experts. Participants conscientiously completed 169 online questions in total, resulting in a complete dataset.

The study's portrayal of the organizational elements linked to AI adoption in the construction sector is one important feature that distinguishes it from earlier research attempts. This study offers a new viewpoint by using EFA and CFA, techniques that have not been widely applied in the literature found during the Systematic Literature Review (SLR). In particular, the implementation of CFA improves the accuracy and reliability of construct measurement. As a result, it enhances our comprehension of the fundamental elements of these structures and their complex interactions with AI in the construction sector.

A four-part cluster made up of creative organizational culture, competency-based development, group decision-making, and strategic analysis was revealed by the EFA's findings. These characteristics are crucial to understanding the dynamics of AI adoption in the construction industry. Notably, the CFA was crucial in determining the measurement model's suitability and testing for convergent validity, highlighting the accuracy and rigor of the study's conclusions. With a p-value of 0.001, innovative organizational culture and competence-based growth stood out as highly noteworthy.

Future research should aim to solve such limitations as this study advances the conversation on AI usage in the construction industry. Researchers should specifically work to increase the breadth of their systematic literature reviews and get over the restrictions imposed by geographic boundaries. Future research might also look into the feasibility of using the Delphi method to elicit expert-based opinions and promote agreement on the organizational aspects linked to AI adoption in the construction sector. By including the perspectives of subject-matter specialists, this collaborative method would offer a comprehensive understanding of the matter.

Limitations

Although the study's main objective has been accomplished, it is crucial to identify some restrictions that affect the applicability of the inferences made from the results. Notably, the viewpoints and thoughts of Pakistani construction industry professionals are the only ones included in this research. Therefore, any conclusions and interpretations drawn from the study's findings should be placed within the context of Pakistan's particular environment and circumstances. It is crucial to note that the literature evaluation procedure for this study was limited in a number of different ways. It specifically targeted specified categories of papers, narrowed the range of publication years, and concentrated on particular databases. These limitations add a boundedness component to the study's knowledge base, which could affect how generalizable its conclusions are to a larger global or cross-temporal context.

RECOMMENDATIONS

Following are some suggestions made based on the study's findings.

- Organizations should think about changing their traditional work culture to make AI integration easier. Due to the valuable capabilities it offers, boosting productivity, sustainability, and efficiency across construction companies and projects, this change is crucial.

- To improve the knowledge and proficiency of employees, it is advisable to incorporate learning resources and programs for skill development related to AI.
- Additionally, senior management should actively include staff in developing adoption strategies for AI.

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