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BIBLIOMETRIC ANALYSIS AND CRITICAL REVIEW OF THE ARTIFICIAL INTELLIGENCE ADOPTION FACTORS IN CONSULTING QUANTITY SURVEYING FIRMS

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ABSTRACT

AI adoption will help Malaysian construction organisations, including Consulting Quantity Surveying (CQS) firms, cope with challenges and increase productivity. However, AI adoption by CQS firms faces adoption issues in Malaysia. Existing AI adoption studies discuss barriers in developed countries. Applying these studies' results in developing countries such as Malaysia is inappropriate, as construction industry practices and properties differ. Also, there is limited attention to factors affecting AI adoption. Existing studies on AI adoption in Malaysia are limited, and the stages of AI adoption have not been rigorously studied. The first objective of the study is to explore and categorise the factors of AI adoption and provide in-depth insights into the different AI adoption stages. The second objective is to identify 62 factors that affect the four stages of AI adoption and group them into four clusters. This study applied Systematic Literature Review (SLR) to identify and classify factor clusters based on the Diffusion of Innovation Theory and Technology Organisation Environment (TOE). The identified cluster of factors can be useful to decision-makers for conducting analyses of AI adoption stages and for formulating adoption strategies, by providing facts and observations within organisations. The review observes that factors affecting AI adoption stages vary across regions, due to governmental pressure, cultural differences, practices, and demographics.

Keywords: Artificial Intelligence (AI), Systematic Literature Review (SLR), Bibliometric Analysis, Factors, AI Adoption Factors, Consulting Quantity Surveying Firms

1.0 INTRODUCTION

The construction industry is grappling with systemic challenges spanning human resources, governance, economic pressures, and technological deficiencies, resulting in significantly hampered growth and low productivity compared to sectors like manufacturing (Aghimien et al., 2021; Oke et al., 2023). Consulting Quantity Surveying (CQS) firms, which operate at the core of project financial control and cost management, are directly impacted by this inefficiency. Construction remains one of the world's least digitalised industries, characterised by a pervasive cultural resistance to change (Blanco et al., 2023). This reliance on manual, non-digital processes complicate project management. It directly leads to inefficiencies in cost control, project delays, diminished quality, and uninformed decision-making—all core functions of CQS practices (Zulu et al., 2023). Given mounting pressures from labour shortages, the impacts of the COVID-19 pandemic, and the demand for sustainable infrastructure (Stride et al., 2023), expediting digital transformation is now a necessity for CQS firms to maintain relevance and competitive advantage.

Artificial Intelligence (AI) has emerged as a leading digital solution that drives advancements in business operations and industry productivity across various sectors (Jan et al., 2023). The adoption of AI techniques, including machine learning, optimisation, and natural language processing, facilitates crucial automation and yields significant competitive advantages over traditional methods (Singh et al., 2023). These tools offer powerful capabilities for data-driven decision-making essential for managing complex financial scenarios. For instance, the manufacturing sector's embrace of Industry 4.0, powered by AI, has yielded substantial improvements in process efficiency, cost reduction, and sustainability (Plathottam et al., 2023). Despite facing acute project management and cost control challenges, the CQS sector has yet to fully capitalise on these substantial AI-driven benefits (RICS, 2024).

Decades of research have demonstrated the potential of AI applications in addressing construction-specific challenges, many of which directly concern the work of CQS firms. Machine learning, for example, shows promise in improving cost estimation, risk prediction, and supply chain optimisation, while knowledge-based systems could aid in tender evaluation and risk assessment (Adeloye et al., 2023). Despite these demonstrated advancements, the construction industry remains highly undigitalised (Albaz et al., 2018). Studies consistently identify numerous adoption barriers directly relevant to CQS firms: cultural resistance, high initial investment costs, concerns around data trust and security, and talent shortages (Prabhakar et al., 2023).

Consequently, the objective of this Systematic Literature Review (SLR) is to provide a bibliometric analysis and a detailed explanation of AI adoption research in CQS firms and empirically examine the factors affecting AI adoption. The contributions of this SLR are defined as follows:

- To provide a bibliometric analysis of AI adoption literature.
- To explore the major factors affecting AI adoption.
- To provide an in-depth description of the different stages of AI adoption

This SLR is organised as follows: Section 2 discusses related work and existing studies on AI adoption to provide a current state of AI in the literature. The systematic literature review protocols and methodologies are described in Section 3. Section 4 provides bibliometric analysis results. Section 5 explains the factors identified in this study. Section 6 discusses the themes in the literature and classifies them by AI adoption stage. The foundational frameworks and key contributions are presented in Section 7. Finally, Section 8 discusses the implications and future direction.

2.0 RELATED WORKS

This section discusses reviews and analyses of the existing literature on AI adoption. Several studies investigated AI adoption between 2019 and 2024, including literature reviews. Current AI adoption studies addressed the adoption barriers and drivers in the construction industry (Abioye et al., 2021; Tjebane et al., 2022; Oluleye et al., 2023; Singh et al., 2023 Zabala et al., 2023; Felemban et al., 2024; Ghimire et al., 2024; Liang, 2024; Shamsiri et al., 2024; Ugural et al., 2024). A study by Na et al. (2023) analyses factors influencing workers in construction-related companies in South Korea and the United Kingdom regarding their intention to use AI-based technologies. However, this study is culturally specific and applies only to the contexts of British and Korean construction workers. Another survey by Delgado et al. (2019) identified the challenges of robotics and automation systems in Europe. However, perceptions of small and medium design organisations are not covered. A few studies discuss AI readiness and acceptance in organisations and identify AI adoption inhibitors that hinder broader-scale adoption (Wang et al., 2021; Ghimire et al., 2024). Similarly, most studies discussed AI adoption at the individual level, such as AI adoption by architects and engineers in their individual capacity, rather than at the organisational level (Cisterna et al., 2022; Wafta et al., 2022; Shang et al., 2023). However, organisational-level AI adoption studies in CQS firms are limited. FakhrHosseini et al. (2024) investigate the existing adoption theories and propose a model to identify factors affecting recent technological advancement. A study on forefront technologies such as the Internet of Things (IoT) and smart connected objects is conducted by Attié & Meyer-Waarden (201[illegible]), which discusses that there are many stages of technology adoption, for example, awareness, interest, evaluation, and trial. These terms are confused in the literature and need clarification and definition.

In contrast to existing reviews that focused on adoption factors and barriers, which were found to be disjointed across studies, this review provides a bibliometric analysis and a more comprehensive overview of AI adoption studies in CQS firms. Furthermore, it explores and categorises the major factors affecting AI adoption at each stage of the adoption process. The other contribution of this review is the categorisation of research by technology adoption stages, such as awareness, interest, evaluation, trial, and confirmation. This SLR is intended to form the basis for future research in the AI adoption domain.

3.0 METHODOLOGY

The research methodology consisted of guidelines to follow for systematically planning and analysing the studies. This study is guided by the research methodology for conducting SLR by Kraus et al. (2022). The research methodology is followed by defining the research questions and using an appropriate search string to extract studies from databases. Also, inclusion and exclusion criteria are defined for quality assurance in SLR. The complete picture of the review strategy is shown in Figure 1.

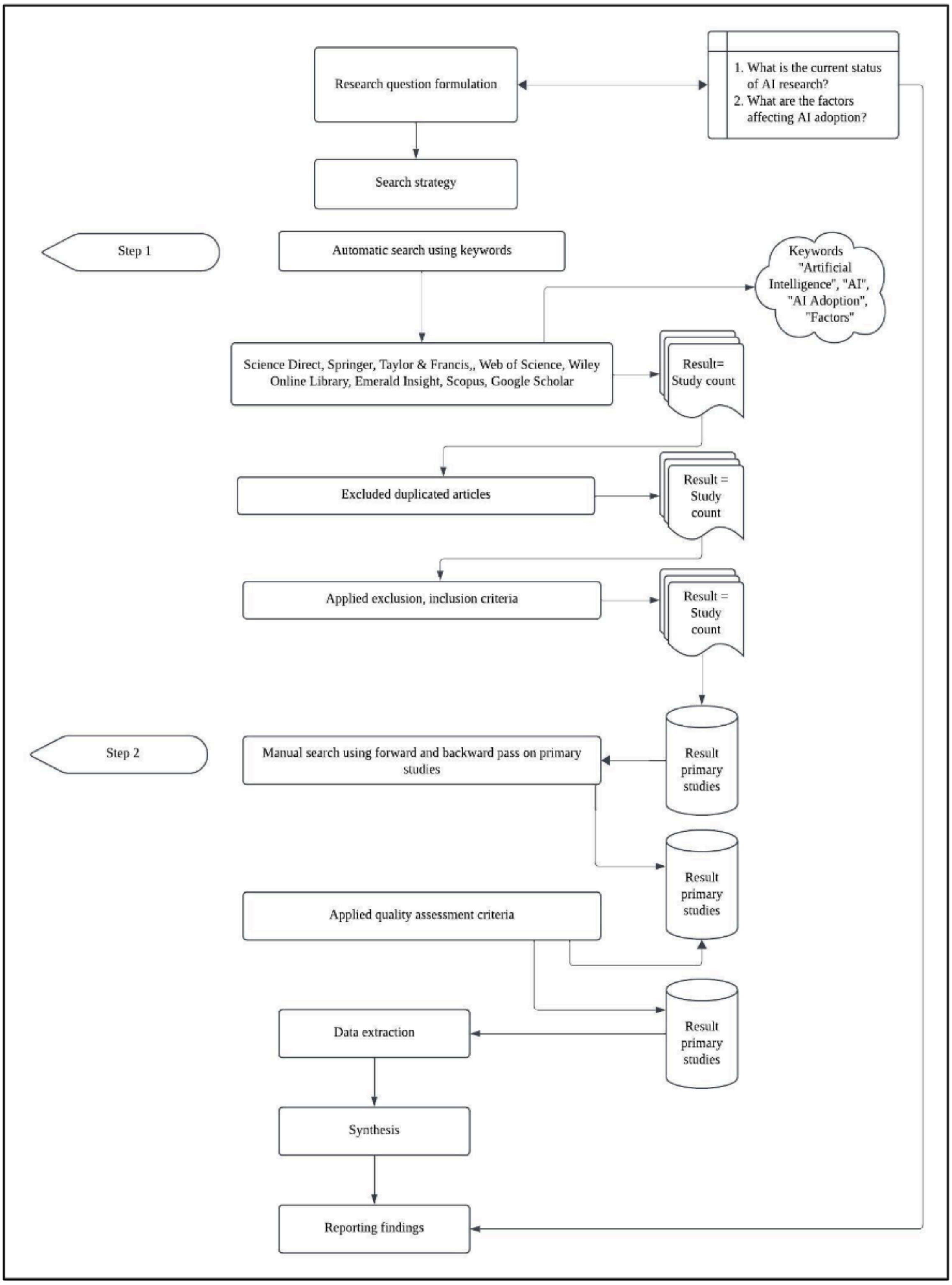

Figure 1: Review strategy of AI SLR

3.1 Data Sources

The review process began with formulating the research question, selecting databases, and analysing current studies. The methodology in this SLR also relies on the selection of study resources (such as ScienceDirect, Springer, Web of Science, Google Scholar, Emerald Insight, Taylor & Francis, Scopus, and Wiley Online Library). A list of research questions is addressed in Figure 1. It is followed by the selection of primary studies, application of inclusion criteria, and synthesis of results.

3.2 Search Strategy

This SLR covered the range of papers from 2019 to 2024. Several studies published before this period generally discuss the applications of AI in different sectors of the construction industry. Based on research questions, keywords are formulated for the search strategy. The terms 'Technology adoption', 'Artificial Intelligence', 'AI', 'AI Adoption, 'Factors', ' Challenges', 'Barriers', 'Quantity Surveying', 'TAM', 'TOE', 'UTAUT', 'DOI' are used as main keywords. The logical operators 'AND' and 'OR' are used to combine keywords. After several attempts, we use the following search string, most suitable for extracting studies: ('Artificial Intelligence' OR 'AI' AND 'Quantity Surveying' OR 'Construction Industry' OR 'Factors' OR 'Adoption Theories'). After that, a manual search is also performed as a forward pass and backward pass to include the most cited and relevant studies that were not covered in the automatic search. The extraction process is shown in Figure 2.

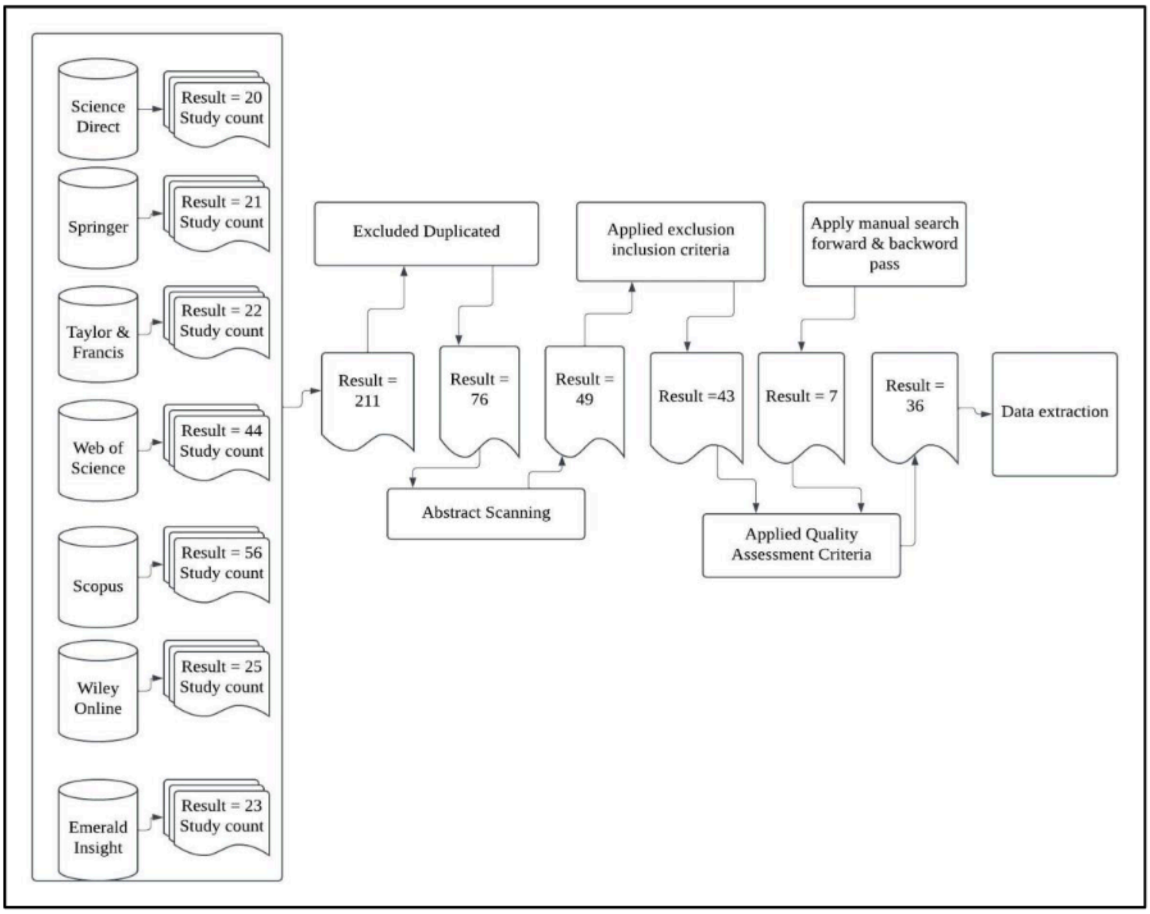

Figure 2: The review extraction process

3.3 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria specified the studies to be included in the SLR. This method ensures that relevant studies are included in an SLR and that irrelevant studies are omitted. This research study included only the studies from the AI domain within the construction industry. The research articles from reputable journals and conferences were selected for review. The duplicated studies are removed. Only studies published in English from 2019 to 2024 are included. The inclusion and exclusion criteria for this study are shown in Table 1.

Table 1: Inclusion and exclusion criteria for AI SLR

Inclusion	Exclusion
Studies that clearly defined adoption variables	Study not using any technology adoption construct
Technology Adoption Studies in Artificial Intelligence	Studies that only focus on applications of AI
Included only full-text studies	Not published in a peer-reviewed journal or conference
Studies published between 2019 and 2024	Not in English
Literature only in the above-selected databases	Literature out of the selected time frame
Written in English	Duplicate studies

3.4 Quality Assessment Criteria for AI SLR

Quality assessment is critical for ensuring the worthiness of selected studies (Kraus et al., 2022). Quality instruments were developed, consisting of factors to be checked and verified through questions for each study (Kraus et al., 2020). To check the quality, four quality assessment questions are developed: (1) Is the adoption addressed related to AI in the construction industry? (2) Is the research method clearly described in the article? (3) Is the data collection method mentioned in the studies? (4) Are the data analysis procedures described in the papers? The questions described are applied to 43 extracted studies to ensure the credibility of the article selected.

3.5 Data Extraction

At this stage, data were recorded in Excel sheets, and Zotero was used as a reference manager. It includes elements of study ID, Author, year, country, and publisher; data analysis methods; adoption theories; and study-level factors. The description of the items is shown in Table 2.

Table 2: Data extraction sheet

Elements	Descriptions
Author	Name of author
Year	Year of publication
Country	Country of research
Publisher	Journal/Conference Name
Study methods	The method applied, such as a survey or an interview
Adoption theories (if any)	Adoption theory/model applied
Study level	Individual or organisational level
Factors	Factors influencing adoption

4.0 CONTENT ANALYSIS

This section discusses the findings of the bibliometric analysis. Results include the study sources, publication outlets, and year-to-year distribution of studies. Also, the country-specific distribution of studies is provided.

4.1 Publication Source

As shown in Figure 3, the majority of the studies are from high-quality journals and reputable conferences, which increases the reliability of the included studies. Thirty-four journal articles (94%) and two conference papers (6%) were included in the review. The analysis shows that the number of journal publications is increasing relative to that of proceedings.

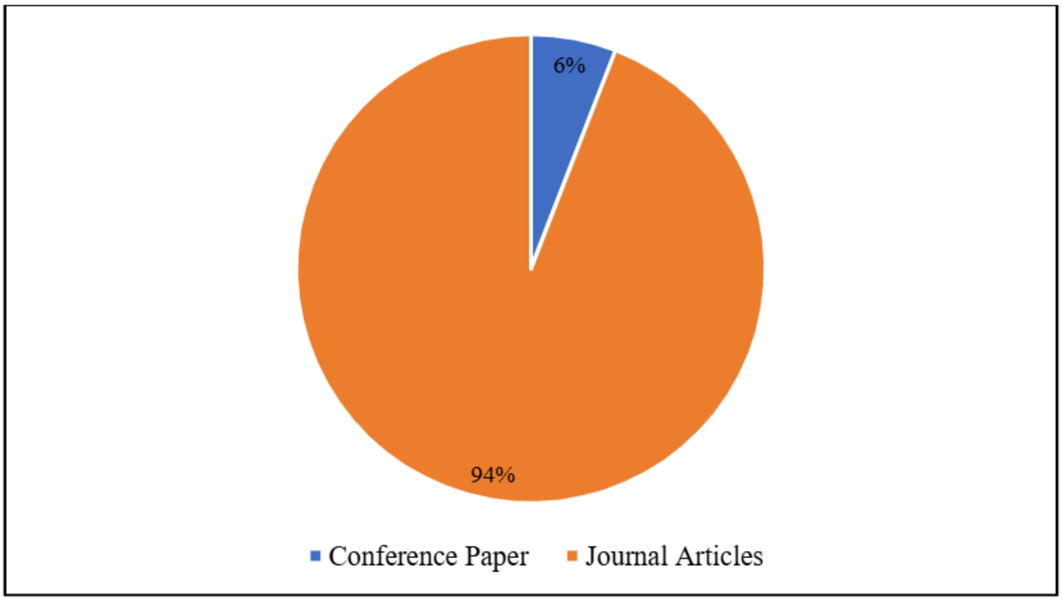

Figure 3: Publication source of AI research

4.2 Distribution of Studies Year-wise

The review includes studies ranging from 2019 to 2024. The distribution of studies is shown in Figure 4. The graph shows a gradual increase in the number of studies published from 2019 to 2024. The highest number of publications is recorded in 2024 (36%). In 2019, the number of publications was at a minimum (3%). A slight decrease in publications is recorded in 2022 (11%). The research themes covered in these studies are technology adoption, readiness, user perceptions, AI implementation, technology acceptance, and AI diffusion. Also, the year-wise publication of articles and publication sources is shown in Figure 4.

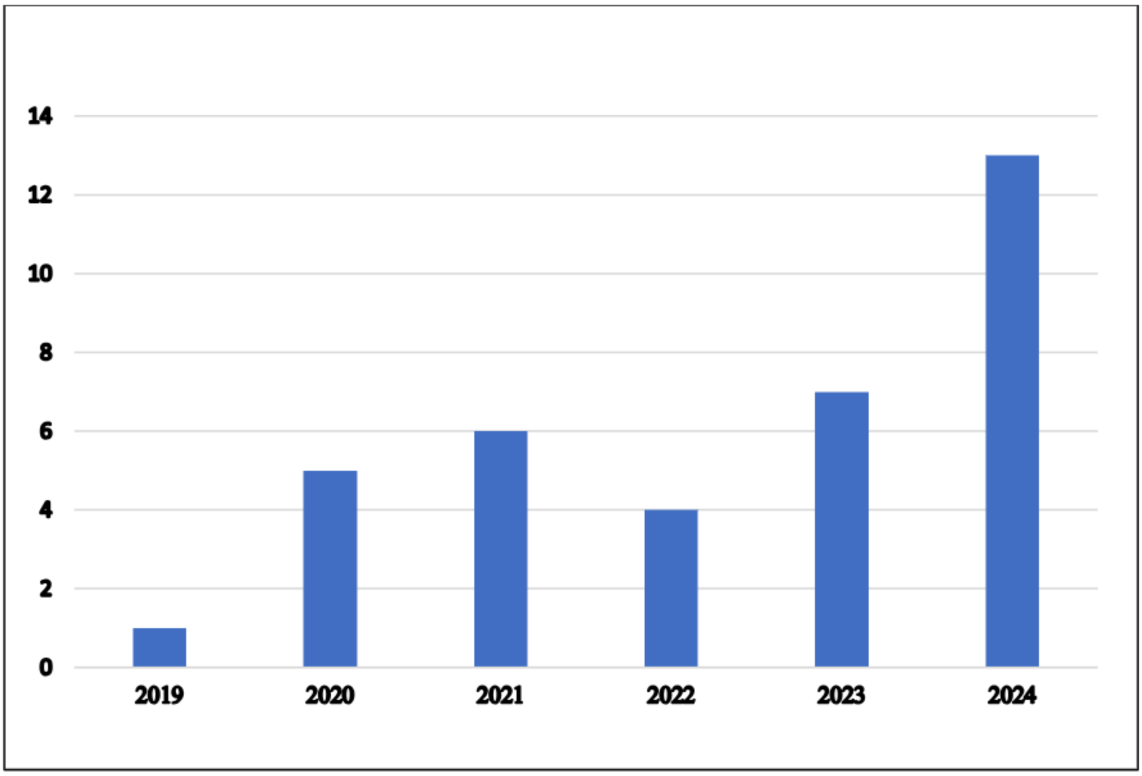

Figure 4: Publication trending of AI research

4.3 Publication Outlets

As shown in Table 3, the most AI articles are published in Automation in Construction and Building (19%), the leading journal. After that, the Building published six studies (17%), while other journals and conferences published a limited number of papers. This result shows that innovation- and sustainability-oriented journals are a priority for publishing. On the other hand, publications concerned with project management journals have the lowest percentage. This would also demonstrate a pervasive pattern in the existing literature and may be interpreted as reflecting the related priorities of the studies presented in such journals.

Table 3: Publication outlets and year-wise distribution of articles

Publication Source	2019	2020	2021	2022	2023	2024	Total
Ain Shams Engineering Journal	0	0	0	0	0	1	1
Automation in Construction	0	0	3	1	0	3	7
Building	0	1	0	0	2	3	6
Built Environment Project and Asset Management	0	0	0	0	1	0	1
Cleaner Engineering and Technology	0	0	0	0	1	0	1
Engineering, Construction and Architectural Management	0	0	0	1	0	2	3
IEEE Access	0	1	0	0	0	1	2
International Symposium on Automation and Robotics in Construction	0	0	0	1	0	0	1
Technology and Innovation in Building Designs	0	1	0	0	0	0	1
Journal of Building Engineering	1	1	1	0	0	0	3
Journal of Open Innovation: Technology, Market, and Complexity	0	0	0	0	1	1	2
Malaysian Construction Research Journal	0	1	0	0	0	0	1
Operations Management Research	0	0	0	0	1	0	1
Results in Engineering	0	0	0	0	0	1	1
Smart and Sustainable Built Environment	0	0	1	0	0	1	2
Sustainability	0	0	1	0	0	0	1
Sustainable Production and Consumption	0	0	0	0	1	0	1
Frontiers in Built Environment	0	0	0	1	0	0	1
Total	**1**	**5**	**6**	**4**	**7**	**13**	**36**

4.4 Country-Wise Publications

The country-wise overview of publications identifies the gaps in research in particular areas. The background of the research relates to the nation or area where the data is gathered. The second consideration for the study's affiliation is the place of the case tested. As depicted in Figure 5. Most of the research has been conducted in Malaysia from 2019 to 2024. After Malaysia, the maximum number of publications is from China. The majority of the listed countries have very low publication counts, with most having only one or two publications.

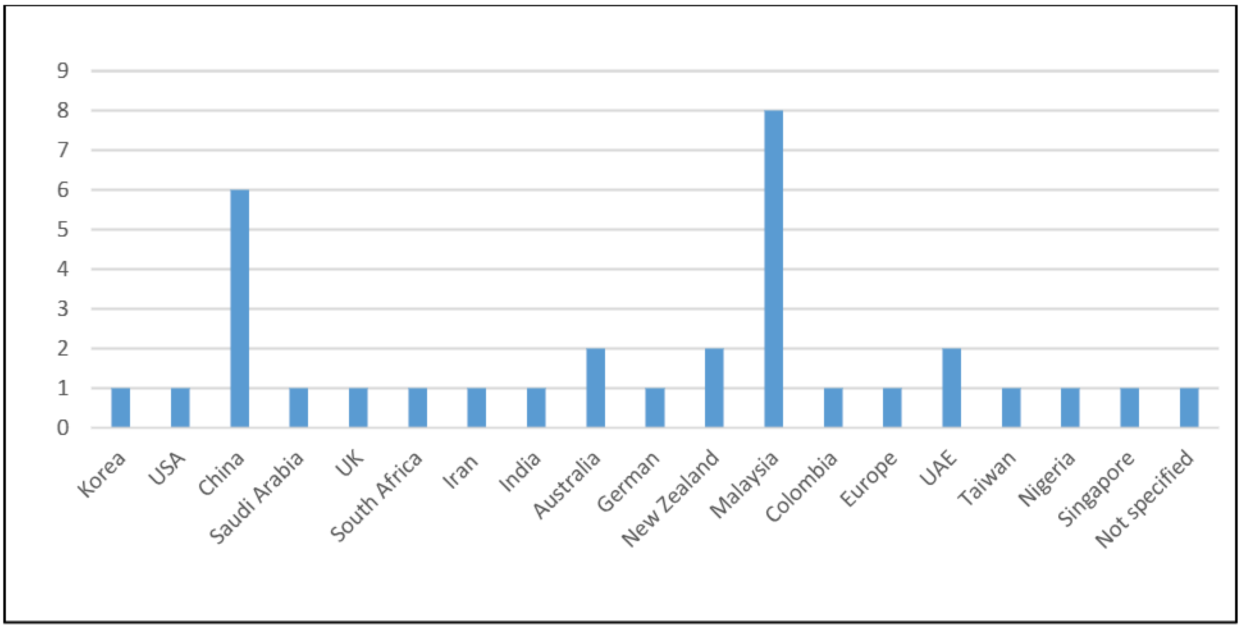

Figure 5: Country-wise AI research

5.0 ANALYSIS OF FACTORS AFFECTING AI ADOPTION STAGES

This section discusses the factors affecting AI adoption in CQS. Factors affecting AI adoption are categorised into four dimensions, including individual, organisational, technological, and environmental.

5.2 Individual Dimension Affecting Awareness and Interest in Adopting AI

Individual awareness and interest in adopting AI is a dynamic process where a person moves from basic knowledge to active engagement. It has been influenced by their perceptions of AI, their motivations for using it, their readiness to adapt, and their overall acceptance of the technology. According to the studies analysed, two factors are most strongly affecting awareness and interest in adopting AI. First is resistance to change (Abioye et al., 2021; Almatari et al., 2024; Felemban et al., 2024; Lada et al., 2023; Oluleye et al., 2021) and the second is lack of top down support (Felemban et al., 2024; Lada et al., 2023; Shang et al., 2023; Ugural et al., 2024). On the other hand, algorithmic challenges and incompatibility (Regona et al., 2022; Shamsiri et al., 2024; Singh et al., 2023; Zabala et al., 2023) are affecting AI awareness and interest, as shown in Table 4. Other important factors include social influence, perceived ease of use, perceived usefulness, lack of trust, time-consuming data entry, and fear of job loss (Na et al., 2023; Singh et al., 2023; Wang et al., 2020). The factors are summarised in Table 4.

Table 4: Individual factors affecting awareness and interest in adopting AI

Individual factors	Author
Social influence	Na et al., 2023
Perceived ease of use	Na et al., 2023, Singh et al., 2023
Perceived usefulness	Na et al., 2023
Lack of top-down support	Felemban et al., 2024, Lada et al., 2023, Shang et al., 2023, Ugural et al., 2024
Resistance to change	Abioye et al., 2021, Almatari et al, 2024, Felemban et al., 2024, Oluleye et al., 2021, Lada et al., 2023
Lack of trust	Wang et al., 2021
Incompatibility	Regona et al., 2022, Zabala et al., 2023
Time consuming for data entry	Wang M et al., 2020
Algorithm challenge	Regona et al., 2022, Shamsiri et al., 2024
Fear of job loss	Liang et al., 2024

5.3 Organisational Dimension Affecting Decision to Adopt AI

Organisational factors are related to inter-organisational processes, practices, and policies that affect AI adoption. Many factors are identified in studies on AI adoption, as summarised in Table 5. The most affecting factor is talent shortages. CQS firms struggle to find personnel with the essential blend of domain knowledge in quantity surveying and AI technical skills, slowing the development and operation of specialised AI tools for tasks such as cost estimation.

Another important factor is top management support and cultural issues. Cultural issues such as fear of job displacement, distrust of AI, and resistance to change hinder AI adoption in organisations. Without a clear, visible, and sustained mandate from senior CQS leadership (partners and directors), AI initiatives risk being treated as peripheral experiments rather than as core business strategy. Leadership commitment is essential to providing the financial security needed, championing transformation across departments, and ensuring the AI strategy aligns with the firm's long-term competitive advantage. Other factors that affect AI adoption are high initial costs, organisational readiness, and financial constraints.

Table 5: Organisational dimension

Organisational dimension	Author
Organisational competence	Na et al., 2023
Lack of infrastructure	Chen et al., 2024, Oluleye et al., 2023, Wang et al., 2021
Insufficient fund	Chen et al., 2024, Wang et al., 2021,
Top management support	Basaif et al., 2020, Felemban et al., 2024, Lada et al., 2023, Pan 2020, Shang et al., 2023, Ugural et al., 2024,
Talent shortage	Abioye et al., 2022, Akinosho et al., 2020, Almatari et al., 2024, Cisterna et al., 2022, Delgado et al., 2019, Mahusin et al., 2024, Shang et al., 2023
Cultural issue	Abioye et al., 2022, Almatari et al., 2024, Chen et al., 2024, Delgado et al., 2019, Mahusin et al., 2024, Oluleye et al., 2023,
High initial cost	Abioye et al., 2022, Delgado et al., 2019, Shang et al., 2023,
Ineffective life cycle management	Oluleye et al., 2023
Organisational readiness	Lada et al., 2023, Shang et al., 2023, Pan, 2020 Tjebane et al., 2022, Ugural et al., 2024
Firm size	Tjebane et al., 2022
Workplace relationships among staff	Tjebane et al., 2022
Information processing management	Tjebane et al., 2022
Knowledge and standard	Tjebane et al., 2022
Collaborative	Tjebane et al., 2022
Attitude to innovation	Tjebane et al., 2022
Cost to the organisation	Ghimire et al., 2024, McNamara& Sepasgozar, 2021, Tjebane et al., 2022,
Risk cost associated with the organisation	Singh et al., 2023Tjebane et al., 2022
Multi-point responsibility	Akinosho et al., 2020
Non-standardisation of construction projects	Akinosho et al., 2020
Employee adaptability	Lada et al., 2020
Easy access to labour	Delgado et al., 2019
Decision-making conflict	Liang, 2024
Resources availability	Abdul-Samad et al., 2024

5.4 Technological Dimension Affecting Implementation and Confirmation to Adopt AI

For CQS firms, the adoption of AI is heavily influenced by technological factors related to the tools themselves, with data challenges, compatibility, and relative advantage being the most critical (as detailed in Table 6). The primary hurdle is data-related challenges, which span everything from ensuring sufficient data availability (e.g., historical project costs) and data reliability to managing the complexity of data interoperability across different platforms (e.g., BIM, traditional spreadsheets).

Crucially, this category includes issues like data complexity, data transparency, and the risk of data hallucination from generative AI models. Furthermore, compatibility is paramount; AI tools for CQS must ensure that the data schemas used during model training (e.g., classifying building elements) are identical to those used during deployment for new projects, as incompatible formats will inevitably lead to errors in cost prediction and project failure.

Finally, relative advantage determines organisational buy-in, as CQS firms must clearly perceive that implementing AI offers substantial, demonstrable benefits such as faster tendering or more accurate risk assessment compared to their existing manual methods.

Table 6: Technological dimension

Technological dimension	Author
Compatibility	Na et al., 2023, Regona et al., 2020, Singaram et al., 2021
Computing power and connectivity	Abioye et al., 2022
Data availability	Aluleye et al., 2023, Akinosho et al., 2020, Wang M et al., 2020
Data maintenance	Shang et al., 2023
Exploitation by hacker	Singh et al., 2023
Data privacy	Chen et al., 2024, Liang et al., 2024, , Mahusin et al., 2024, Paneru & Jelani, 2021, Singh et al., 2023, Zabala et al., 2023
Uncertain function of the AI algorithm	Shamsiri et al., 2024, Singh et al., 2023,
Black box	Akinosho et al., 2020, Regona et al., 2020
Data protection	Akinosho et al., 2020, Liang et al., 2024, Wang M et al., 2020
Data reliability	Mc Namara & Sepasgozar, 2021, Regona et al., 2020
Data complexity	Almatari et al., 2024, Watfa et al., 2022
Unproved effectiveness	Delagado et al., 2019
Data interoperability	Ghimire et al., 2024, Singaram et al., 2021, Qureshi et al., 2020,
Data management	Ding, 2020, Shamsiri et al., 2024 Singaram et al., 2021,Shamsiri et al., 2024, Wang M et al., 2020
Data validation	Wang M et al., 2020
Data transparency	Liang et al., 2024
Data accuracy	Ghimire et al., 2024
Data generalisability	Ghimire et al., 2024
Data hallucination	Ghimire et al., 2024
Relative advantage	Chen et al., 2024, Delgado et al., 2019, Pan et al., 2020, Singh et al., 2023

5.5 Environmental Dimension Affecting AI Adoption

In the context of AI adoption by CQS firms, environmental factors, such as the external forces and conditions, introduce significant complexities. The two most dominant external concerns are cybersecurity risk and the legal environment (as summarised in Table 6). AI adoption inherently increases cybersecurity risks, exposing CQS firms to threats such as data poisoning (the compromise of historical cost data), adversarial attacks on prediction models, and the potential theft of proprietary AI models. Mitigating these threats requires CQS firms to implement robust security measures, including advanced data encryption and strict access controls to protect sensitive client and project information. Simultaneously, the legal environment poses substantial adoption challenges, including navigating evolving data privacy regulations, addressing ethical concerns about algorithmic bias in estimation and risk tools, and managing intellectual property rights for internally developed AI models. The current lack of clear legal frameworks surrounding AI operations increases the risk of legal and financial repercussions. Other crucial external considerations include managing competitive pressure from rival firms, navigating the availability of regulatory support, and benefiting from direct government support for technological transition.

Table 6: Environmental dimension

Environmental dimension	Author
Ethical guidelines	Abioye et al., 2021, Akinosho et al., 2020, Ghimire et al., 2024
Fragmented industry	Chen et al., 2023, Ghimire et al., 2024, Regona et al., 2022, Singaram et al., 2023 ,
Legal environment	Abdul-Samad et al., 2024, Almatari et al., 2024, Chen et al., 2023, Delgado et al., 2019, McNamara & Sepasgozar, 2021, Singaram et al., 2023,
Lack of interest from the client	Chen et al., 2023
Lending restrictions	Chen et al., 2023
Competitive pressure	Lada et al., 2024, Pan, 2020, Tjebane et al., 2024
External support	Lada et al., 2024
Lack of government incentives	Delgado et al., 2019
Decreasing public infrastructure budget	Delgado et al., 2019
Support of the government	Felemban et al., 2024
Government pressure	Tjebane et al., 2024
Construction regulatory	Ghimire et al., 2024, Tjebane et al., 2024,
Lack of standards	Almatari et al., 2024
Cybersecurity risk	Abioye et al., 2021, Akinosho et al., 2020, Ghimire et al., 2024, Liang et al., 2024,Regona et al., 2022, Singh et al ., 2023, Wang et al., 2021

6.0 DISCUSSION OF AI RESEARCH THEMES

This section provides detailed descriptions and categorisation of themes found across different studies, based on adoption stages, as shown in Figure 6.

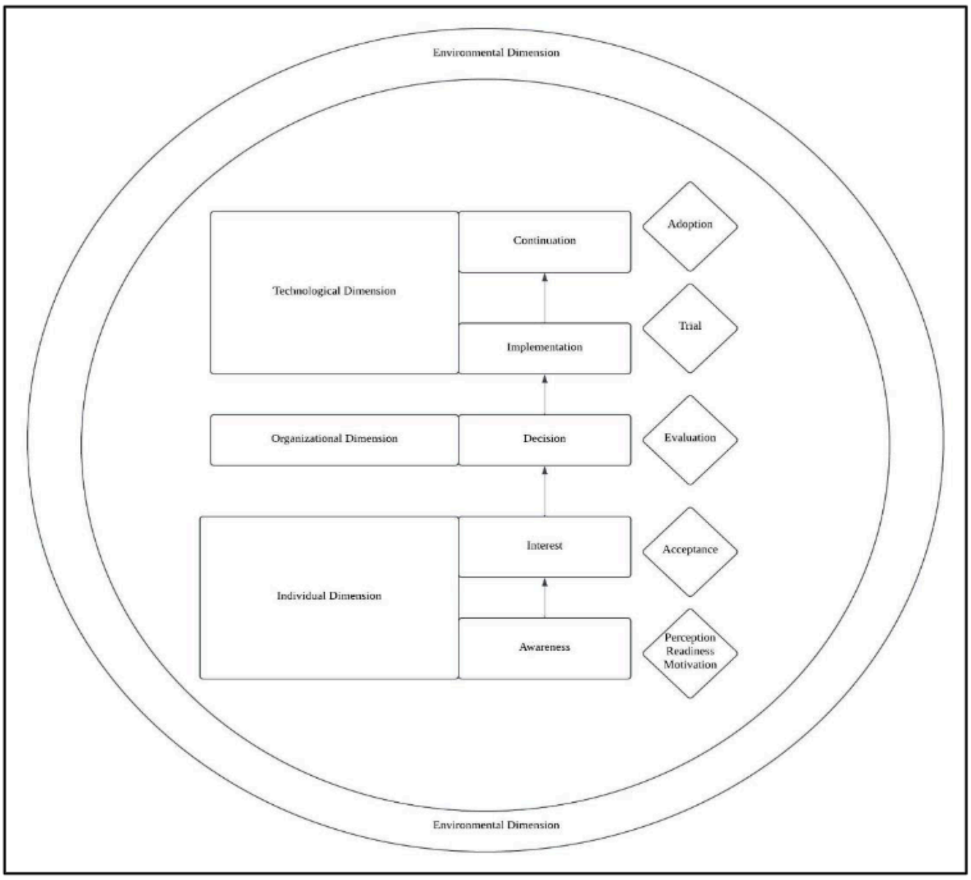

Figure 6: AI adoption research themes

6.1 AI Awareness

In the individual dimension of AI adoption, awareness serves as the foundational step, encompassing perception, motivation, and readiness. Individuals must first perceive AI's relevance and potential benefits to their tasks or lives, understanding how it differs from existing tools. This perception is shaped by clear communication and education, which dispel myths and showcase practical applications. A study by Na et al. (2023) reveals that perceived usefulness positively influences technology satisfaction and usage intention in both South Korea and the UK. Moreover, perceived ease of use positively impacts perceived usefulness and satisfaction. Not only that, but technology satisfaction significantly influences usage intention. Divergences were observed in the influence of personal competence and social factors. In South Korea, personal competence primarily affects perceived ease of use, whereas in the UK, it influences both perceived ease of use and perceived usefulness. Motivation arises from seeing AI's value in improving efficiency, productivity, or personal growth. Demonstrating how AI can solve specific problems or enhance existing workflows is crucial. A notable finding by Cisterna et al (2022) is that construction professionals with AI experience generally reported positive experiences with AI applications.

Participants reported a nearly 78% increase in efficiency due to AI use. The primary obstacle to AI implementation was identified as a lack of AI expertise. Specific AI applications, including Ensun, Neuroflash, and Oculai, were highlighted. Chat-GPT was also used despite concerns about data protection. Positive impacts of using AI included database creation, direct AI application assistance, and the elimination of repetitive tasks. Lastly, readiness involves assessing one's skills and comfort level with AI. Readiness includes providing accessible training resources and fostering a supportive environment that encourages experimentation and learning. Felemban et al (2024), in a study done in China, confirmed that organisational training and development significantly enhance employee skills, mitigate technical challenges, and cultivate a learning culture, all of which are crucial for successful AI adoption. By addressing perception through clear information, sparking motivation by showcasing benefits, and building readiness through accessible education, awareness becomes a powerful catalyst for individual AI adoption.

6.2 AI Interest

Regona et al. (2022) conducted a study to identify challenges in implementing AI in the construction industry. The study's results support market acceptance of AI practices. Also, Abioye et al. (2021) conducted a study to analyse the AI techniques adopted and identify the challenges to their implementation in the construction industry. The study conducted a critical literature review of previous research on the construction industry. Similarly, Na et al. (2022) conducted a Structural Equation Modelling (SEM) analysis to examine the influencing factors of AI-based technology acceptance in the construction industry. The study employed the Technology Acceptance Model (TAM) and Technology Organisation Environment (TOE) framework for the analysis.

6.3 AI Decision

AI-based organisational decision-making in the construction industry is studied by Chen et al. (2024). The study explores the obstacles hindering the widespread integration of digital technologies, including AI, within the construction sector. The study uses a mixed-methods approach, combining quantitative surveys and qualitative interviews to identify key barriers. The findings pinpoint industry standards, client interests, and financial needs as significant impediments. The paper also develops a framework connecting organisational attributes to these perceived barriers, offering insights for academics, practitioners, and policymakers. Ultimately, the research seeks to promote informed decision-making and strategic initiatives that will accelerate the adoption of digital technologies, including AI and improve the construction industry's overall performance and sustainability.

6.4 AI Implementation

Assessing the satisfaction levels of AI stakeholders is essential for the successful implementation of AI in organisations. Delgado et al. (2019) investigate the factors hindering the adoption of robotics and automated systems in the construction industry. Using a mixed-method approach, the research identifies challenges, categorises them into contractor-side economic factors, client-side economic factors, technical and work-culture factors, and weak business case factors, and ranks them by importance. The analysis combines a literature review, focus group discussions with industry experts, and quantitative data from questionnaires. The findings reveal that high initial costs and a lack of a clear business case are significant barriers. The paper also compares its findings with other studies and discusses implications for stakeholders, aiming to inform strategies that mitigate these challenges and encourage the integration of robotics in construction. It identifies the lack of sufficient cost/benefit studies that stakeholders find concerning.

6.5 AI Continuation

Many factors influence the continuation of technology in organisations. Bajpai and Subhas (2022) investigate the implementation and continuation of digitalisation in the Indian construction sector. It employs a PLS-SEM approach to assess the role of various enablers, such as barriers, success factors, and perceived benefits, in the digitalisation process. The study finds that stakeholders' perceived benefits and the addressing of barriers significantly impact successful digitalisation implementation, while risk factors have less influence on its continuation. The research offers a framework for construction firms to understand and navigate the complexities of digital transformation. It emphasises the importance of a comprehensive digital plan and highlights that digitalisation is akin to innovation adoption, requiring both deployment and sustained use. A notable finding is that barriers are essential enablers for effective implementation, while success factors are important drivers of the continued success of digitalisation in the construction sector. Stakeholders' perceived benefit has a substantial role in both implementation and continuance.

7.0 CONCLUSIONS

SLR successfully provided a bibliometric analysis and a detailed explanation of AI adoption research, specifically examining the factors affecting AI adoption in CQS firms. Assessing the AI adoption process and its dynamics is vital to policymakers and adopters at the individual and organisational levels. The underlying purpose of this study is to help construction organisations, including CQS firms in Malaysia, cope with systemic challenges, increase productivity, and address the reality that construction remains one of the world's least digitalised sectors.

7.1 Foundational Frameworks and Key Contributions

Established technology adoption theories systematically guided the structure and findings of this research: the DOI Theory and the TOE framework. The SLR achieved its primary objectives by exploring and categorising the factors influencing AI adoption within this dual theoretical lens.

1. Theoretical-Based Factor Categorisation: The study identified and classified 62 factors into four distinct dimensions or clusters that affect the AI adoption process, grounding the complex reality of AI barriers within the structured domains of TOE and DOI.

- Organisational Dimension (TOE Context): Factors like talent shortages, top management support, organisational readiness, cultural issues (fear of job displacement), and high initial costs. These directly address the internal organisational context, which is crucial to the decision to adopt AI.
- Technological Dimension (TOE Context/DOI Attributes): Dominated by data-related challenges (data availability, reliability, complexity, interoperability), data privacy, and the required computing power. Core DOI concepts, such as compatibility and relative advantage (the demonstrable benefit over manual methods), are paramount here and affect the implementation and confirmation stages.
- Environmental Dimension (TOE Context): External factors such as cybersecurity risk, the legal environment (data privacy, ethical guidelines, algorithmic bias), competitive pressure, and government support. These external pressures and constraints form the environmental context influencing adoption.
- Individual Dimension (DOI Focus): Key factors affecting awareness and interest include resistance to change, perceived usefulness, perceived ease of use, lack of trust, and the fear of job loss. These factors align with individual psychological variables central to the initial phases of technology diffusion.

2. Stage-Based Adoption Framework: The review clarified and categorised research based on the sequential stages of AI adoption—awareness, interest, evaluation, trial, and confirmation/continuation. By providing an in-depth description of these stages, the SLR clarifies terms often confused in the literature, offering a clearer roadmap for CQS firms navigating digital transformation.

3. Contextual Specificity (CQS in Developing Nations): The bibliometric analysis confirmed that factors affecting the AI adoption process vary significantly by region, attributed to governmental pressure, cultural differences,

practices, and demographics. This observation is critical because it highlights why applying AI adoption study results from developed countries is often inappropriate for developing nations, such as Malaysia, where construction industry practices and proprieties differ substantially. This conclusion confirms the need to focus on organisational-level AI adoption studies within CQS firms.

8.0 IMPLICATIONS AND FUTURE DIRECTIONS

The identified cluster of factors is highly useful for decision-makers in CQS firms and the broader construction industry to analyse AI adoption stages and formulate effective adoption strategies. The findings confirm that a single AI adoption approach across all countries may not be feasible.

Given the complex nature of AI adoption identified in this study, the analysis suggests that existing technology adoption models and theories, including DOI and TOE, may need to be revised and extended to accommodate the more complex adoption process associated with AI. Future research is also recommended to utilise multiple data collection methods to gain deeper insights into AI adoption issues, recognising that the diverse nature of organisations and their structures make generalising findings difficult in this rapidly changing field.

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