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# Artificial Intelligence (AI)-Based Technology Adoption in the Construction Industry: A Cross National Perspective Using the Technology Acceptance Model

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**Abstract:** The research has chosen the workers in construction-related companies in South Korea and the United Kingdom (UK) as research subjects in order to analyse factors that influence their usage intention of Artificial Intelligence (AI) based technologies. The perceived usefulness had a positive impact (+) on technological satisfaction and usage intention in terms of the commonalities shown by the construction industry workers in both countries, South Korea and the UK, in adopting AI-based technologies. Moreover, the most remarkable differences were personal competence and social influence when choosing AI-based technologies. It was analysed that in the case of South Korea, personal competence had a positive impact (+) on perceived ease of use, whereas the UK had a positive impact (+) on perceived usefulness and perceived ease of use. This study holds particular significance in the domain of cross-cultural research within the construction industry. It conducts an analysis of the factors influencing the adoption of AI-driven technologies or products, with a specific focus on the cultural differences between two nations: South Korea and the UK, which represent Eastern and Western cultural paradigms, respectively.

**Keywords:** artificial intelligence; construction industry; technology acceptance model; cross culture; structural equation model

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**Citation:** Na, S.; Heo, S.; Choi, W.; Kim, C.; Whang, S.W. Artificial Intelligence (AI)-Based Technology Adoption in the Construction Industry: A Cross National Perspective Using the Technology Acceptance Model. *Buildings* **2023**, *13*, 2518. https://doi.org/10.3390/buildings13102518

Academic Editor: Mohamed K. Ismail

Received: 14 August 2023
Revised: 11 September 2023
Accepted: 26 September 2023
Published: 4 October 2023



## 1. Introduction

The pervasive incorporation of Artificial Intelligence (AI) across diverse industries has emerged as a defining characteristic of the 21st century. AI refers to the field of computer science and technology that focuses on creating and developing computer systems, software, and algorithms capable of performing tasks that typically require human intelligence [1–3]. As AI technologies progressively advance and reach higher levels of maturity, they present unparalleled prospects for fundamentally transforming our approach to intricate challenges within the construction sector. [1,4–8]. AI technologies are revolutionising the construction industry by enhancing efficiency, safety, and project management. One notable application is predictive analytics, which leverages historical data and machine learning algorithms to forecast potential project delays, material shortages, and cost overruns [1,9,10]. Another vital area is autonomous construction equipment, such as self-driving bulldozers and excavators, which streamline excavation and grading processes while reducing labour costs [11–13]. Computer vision systems enable real-time monitoring of construction sites, enhancing safety by detecting potential hazards and ensuring compliance with safety protocols [14–16]. Furthermore, natural language processing and chatbots facilitate streamlined communication and collaboration among project stakeholders, helping to mitigate misunderstandings and delays [1,8,17,18]. Overall, AI technologies are reshaping the construction landscape by optimising operations, reducing risks, and ultimately delivering more cost-effective and efficient construction projects.

In particular, the aforementioned AI-based technologies in the construction industry are being recognised as feasible alternatives to solving the problems of low labour productivity in this industry compared to other industrial sectors [19]. Nevertheless, the reality is that the application of AI-based technologies or digitalisation in the construction industry has been progressing at a relatively slow pace [9,20,21]. In order to overcome such challenges in the construction industry, each county has been promoting various policies to incorporate AI-based technologies [22–24]. For example, the United Kingdom government recognizes the potential of Artificial Intelligence to pre-emptively mitigate issues such as delays and cost overruns in construction projects. As such, they have allocated approximately £18 million for research and development in the construction industry through the 'Industrial Strategy Challenge Fund in Research' [22]. Similarly, the South Korean government is investing heavily in R&D funds to develop smart construction and smart inspection technologies through its 'Smart Construction Roadmap' [23]. Additionally, Singapore has been proactive in integrating Fourth Industrial Revolution technologies into its construction sector, as evident in 'The Construction Industry Transformation Map in 2017', released by the Building and Construction Authority (BCA). This initiative aims to enhance productivity, reduce costs and safety incidents, and create new job opportunities [24]. While numerous countries are increasing investments in AI technologies for construction, the rate of technology adoption varies between nations. This disparity is influenced by various cultural, socio-economic, and institutional differences among countries [25–27]. This article aims to delve into a comprehensive comparative analysis of the acceptance of AI-based technologies within the construction industry in South Korea and the United Kingdom. Understanding the drivers of AI-based technology acceptance in different cultural backgrounds can provide valuable insights for stakeholders, policymakers, and industry professionals looking to optimize their AI adoption strategies.

The purpose of this research was to compare the attitudes towards AI-based technologies applying to the TAM across two different countries: South Korea and the UK. In this article, the quantitative research method was adopted to explore the attitudes, perceptions, and experiences of construction stakeholders, including project managers, engineers, contractors, and laborers, in both South Korea and the UK. By employing this approach, we will identify and analyse the key determinants that contribute to the varying degrees of AI-based technology acceptance in construction practices in each country. This comparative analysis will aid in informing policy initiatives, promoting international collaboration, and fostering innovative approaches to leverage AI's transformative potential effectively. The subsequent sections of this article are organised as follows. The next section of the research entails a theoretical examination of AI-based technologies within the construction industry, as well as a review of the technology acceptance model and relevant theories in terms of TAM. The research model and hypothesis of this study is presented in Section 3. The following section analyses the research model and examines the implications of the comparative results of this study. Finally, the authors present the conclusions of this research in Section 6.

## 2. Theoretical Background

### *2.1. Artificial Intelligence and the Construction Industry*

As we delve into the dynamic landscape of the construction and civil engineering industry, we must acknowledge the substantial transformative changes introduced by AI and machine learning technologies. These have not just reshaped traditional processes but also instigated a new wave of innovation, making the industry more efficient, safer, and sustainable.

A cornerstone of this transformation is Generative Adversarial Networks (GANs). These neural network architectures, marked by their ability to generate data resembling the input, have emerged as game-changers within the industry. In particular, GANs have been extensively applied in constructing 3D reconstruction systems [28]. These systems provide comprehensive 3D visualisations, significantly enhancing project management capabilities and enabling pre-emptive problem-solving [29,30]. Further, GANs have demonstrated substantial predictive capabilities, specifically in welding processes, where their utilisation has optimised electrical conductivity and tensile strength, thereby improving the quality and durability of constructions [31]. Augmented Reality (AR) and Interaction Design (IxD) technologies represent another frontier where AI has played a significant role. These technologies have been instrumental in fostering public participation in urban design and redevelopment projects, contributing to the emergence of more inclusive and collaborative design principles [31,32]. Parametric design instruments, in particular, have catalysed this democratisation, transforming the traditionally top-down urban development approach into a more community-oriented process [33].

The fusion of machine learning with the Internet of Things (IoT) has brought about significant operational efficiency within the construction industry [34]. Automated data collection from construction sites has become possible, reducing human error, improving resource management, and enhancing the timeliness and accuracy of decision-making [35]. Such advancements extend to construction resource and equipment management, where machine learning techniques have been effectively utilised for trajectory prediction of mobile resources and equipment management [36–38].

Moreover, the integration of machine learning in construction planning and scheduling has streamlined these processes, offering substantial economic benefits. Automated methods backed by years of extensive research have proven successful in minimising costly oversights, accelerating project timelines, and increasing project efficiency [31,39–41].

Nevertheless, as these technologies bring numerous advantages, they also raise new challenges, notably in terms of safety and ethics. Safety enhancements have been notable, with advancements in computer vision and Long Short-Term Memory (LSTM) facilitating the development of predictive models for unsafe behaviours in construction sites [42,43]. However, with increasing automation comes ethical considerations. Aspects such as job security, privacy, and accountability need to be thoroughly deliberated and addressed [44]. The implications of machine learning extend to more complex construction processes as well. For instance, when integrated with Building Information Modelling (BIM), machine learning algorithms have simplified processes such as tunnelling [30]. These advancements have led to real-time data analysis, technical procedure automation, and an overall enhancement of construction process efficiency. This integration has also contributed to novel developments in niche sectors such as structural glass engineering [45] and building energy efficiency [35,36,43].

However, despite the transformative impact of AI and machine learning, it is important to recognize that our understanding of these technologies' full potential is still evolving [46,47]. Areas such as additive and subtractive manufacturing still require comprehensive systematic reviews and further research [22]. Improvements are required, particularly in data sensing, collection, and connectivity, to fully leverage AI and machine learning in these areas.

In summary, the role of AI and machine learning in the construction and civil engineering industry is extensive [48,49]. It spans the spectrum from design principles to safety protocols and process optimisation. As we embrace these advancements, it becomes increasingly important to ensure a balance between innovation, safety, and ethical considerations, thereby fostering a sustainable and responsible future for the industry [17,50,51].

### 2.2. Basics of Technology Acceptance Model (TAM)

Since the users' acceptance of new technology is a prerequisite in technological innovation, it is important to reveal the factors in an individual's acceptance and understanding of new technology. The research model broadly utilised to present solutions to these research problems is the technology acceptance model suggested by Davis [52]. The technology acceptance model has its theoretical basis in the theory of reasoned action [53,54] and the theory of planned behaviour [55,56]. The technology acceptance model provides theoretical grounds for the studies that predict the final actions of the users in accepting technology [52,53,55,56].

According to the theory of reasoned action (TRA), the actual action is affected by the behavioural intention to implement, which is decided upon the attitude and subjective norms. Fishbein and Ajzen [53] suggested the TRA model, which asserts that the attitude to action is affected by belief and subjective norms, and the subjective norms are influenced by normative belief and the motive to adopt. In other words, the point of TRA is that the individual's action is predictable when the belief, attitude, and behavioural intention can be found out (See Figure 1).

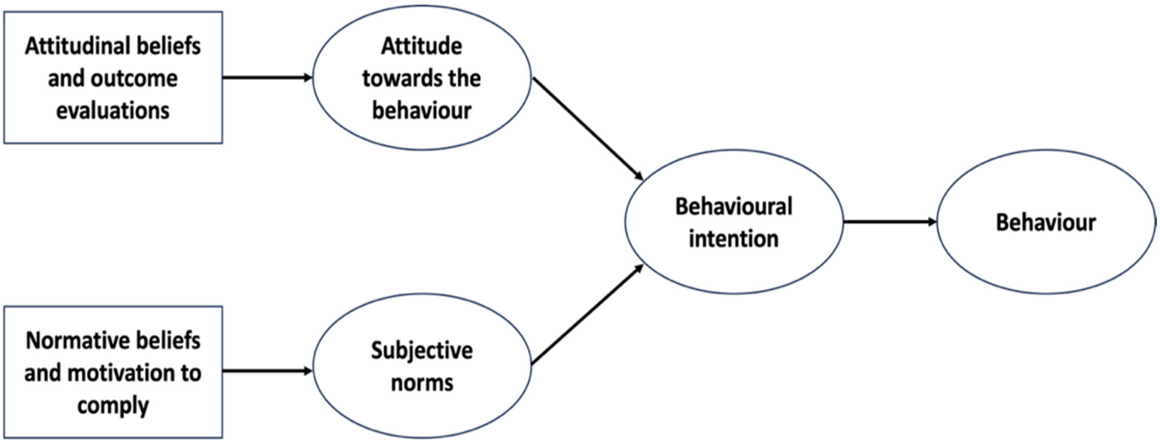


**Figure 1.** Theory of Reasoned Action.

Along with this, the theory of planned behaviour, another theoretical basis for the technology acceptance model, expanded the construct of TRA by adding subjective norms and perceived behavioural control. As shown in Figure 2, TRB asserts that limited action is perceived control through controlling intention; thus, it is likely to not take action when one considers that self-control would be difficult when trying to do something [57,58].

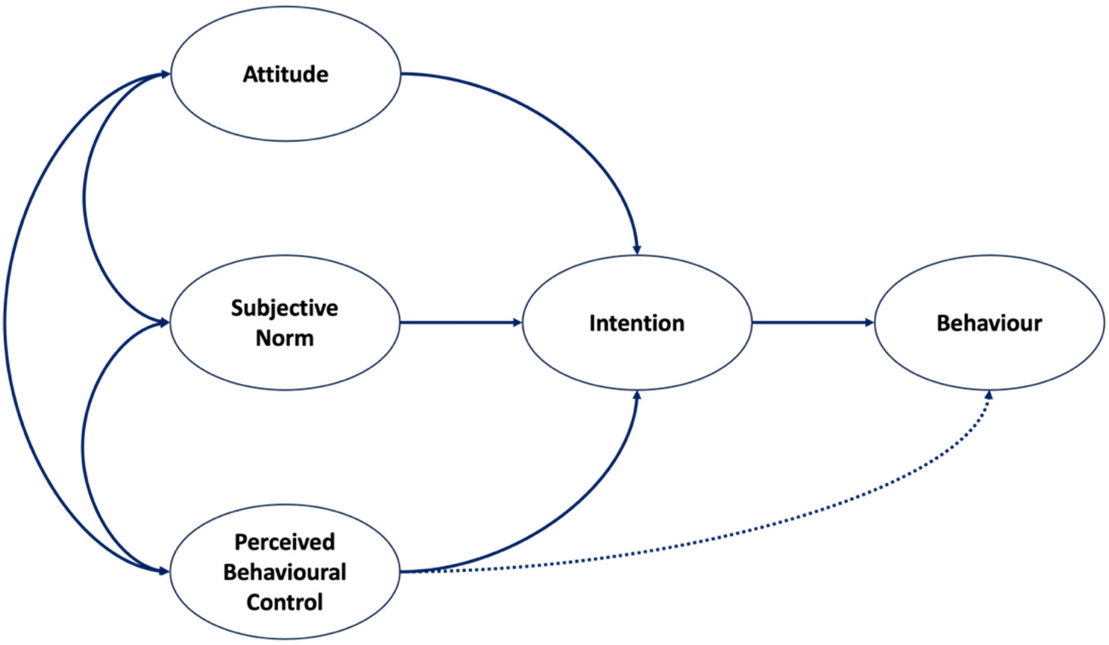


**Figure 2.** Theory of Planned Behaviour model.

As shown in Figure 3, the technology acceptance model is a theory asserting that perceived usefulness and perceived ease of use decide behavioural intention and actual usage [55,56]. Davis defined perceived usefulness as the degree of how much help an individual could receive in work improvement when using a specific system [52]. That is to say, perceived usefulness refers to the evaluation of the enhancement of work productivity and efficiency of users by using new technology. Moreover, perceived ease of use was defined as the ability of a user to utilize new technology or new informational technology without many difficulties [52]. This means that when utilising specific technology, users would be able to utilize new technology at ease without special physical or psychological efforts. The technology acceptance model explains that these two main factors affect the attitude toward utilising technology and the intention to use of the person accepting technology and will lead to the actual selection of technology.

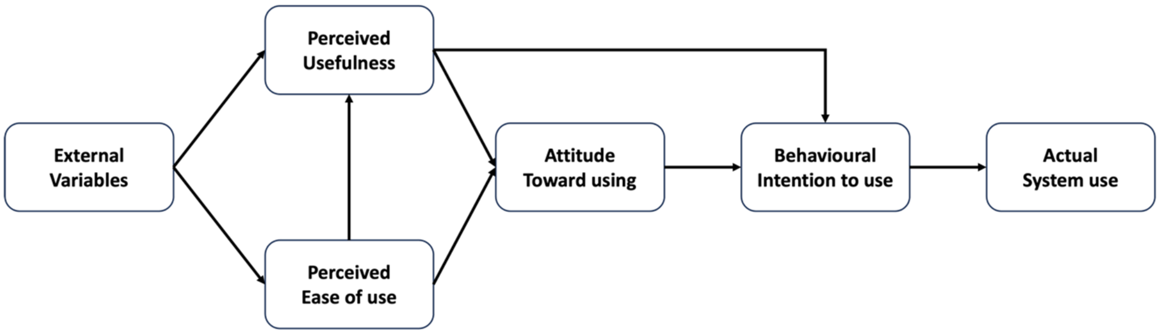


**Figure 3.** Technology Acceptance Model.

Since being suggested by Fishbein and Ajzen [53], TAM went through a theoretical elaboration process and was actively applied as a valuable theory in explaining the selection actions of various groups regarding choosing a new technology or system. The research initiated by targeting specific occupations, such as white-collared or specialised workers who utilize necessary technologies for computer-related work, is gradually adding depth and width [55,59,60]. Based on these works, TAM was internationally utilised by a number of scholars to explain the actions for adopting new digital media after the 1990s. In particular, the researchers in the early stages continuously implemented methodological verification tasks which could stably evaluate each factor through studies improving credibility and validity, so as to improve theory [61–64].

After the model was suggested, preceding research regarding TAM was in a verification study through simple repetition of the model and variable expansion study with various variables added. Particularly, TAM has merits in being able to flexibly add varied external variables. Resulting of these traits, several researchers have expanded external variables to social influence (subjective norms, spontaneity, image, etc.) and cognitive tool process (work relations, result quality, result manifestation, etc.). Furthermore, the subject of application on TAM is widely pertained from product to system [49,52,65–67]. In the case of products, these were utilised as tools to understand the possibilities of application and influencing factors with the advent of new information technology-based devices [68–72]. Moreover, studies on the possibility to succeed and the probability to enter market prior to service launching are being actively carried out.

TAM is being utilised for studying situations such as adopting new information systems or new products in organisations. Since these generally occur involuntarily, the study focuses on understanding how technologies or products are accepted and the procedure. For instance, when new technology is to be introduced in an organisation, TAM enables one to answer questions on why it was accepted, how it is being used, and what influences it has within the organisation. Although TAM is actively applied in introducing new technologies or products within various organisations and forms a theoretical basis, studies on adopting new technologies or products in the construction industry are lacking.

Additionally, most TAM studies target a single country [73–75], and comparative research between the countries is relatively insufficient [76–78]. The research by Straub et al. [77] emphasised the importance of comparative study between the countries and suggested the possibility of internationally applying TAM through comparison among the countries for accepting an information technology called e-mail. In this study, e-mail acceptance was validated in the U.S. and in Switzerland, whereas not in Japan. Similarly, the comparative study on countries applying TAM in the construction industry carried out the study on accepting Building Information Modelling between users in the U.S. and South Korea, by Lee and Yu [79].

AI-based technologies are recognised as core national competence not only to the group of experts but also to the general public [5,17,51,80,81]. While the impact of AI is rapidly spreading through all parts of the industry, competing for AI technology hegemony is fierce around the advanced countries. Nonetheless, there are almost no analyses on the influencing factors on the usage intention between the countries in adopting AI technologies to be utilised in the construction industry. Therefore, the study aims to analyse the impacting factors and investigate the leverage differences between each sector in adopting AI-based technologies in the Korean and British construction industries.

## 3. Research Model and Hypotheses

### 3.1. Research Subject and Method

In order to analyse influencing factors on the usage intention between Korean and British construction industry workers, the study has set the employees of construction-related companies in South Korea and the UK as research subjects. The construction-related companies, which are the study subject, were defined as companies for construction building, architectural design, construction structure design, building maintenance, construction equipment and machinery and construction-related supply chain, and construction-related researchers.

The research has chosen a survey as its study method to verify the set hypotheses. An online survey was selected so as to abide by quarantine regulations due to COVID-19, and to overcome the time and space limits of South Korea and the UK. The survey carried out on the study has conducted preliminary research to verify the relevance of research questionnaires and to develop them. Based on the results of the preliminary study, adjustments to the questionnaires were made, and the actual research was carried out. Preliminary research was conducted through semi-structured interviews with experts in the construction industry, such as university professors of architectural engineering, technicians with over 20 years of experience, and professional engineer license holders. Through this process, professionals have reviewed the validity of the suggested model and variables in the study, and developed survey questionnaires to use based on the results.

The questionnaires used in the research make up a total of three sections. The first section included a brief explanation of the survey's purpose, the definition of AI-based technologies in the construction industry, and the standard for the company size. The second part was made to provide information on gender, level of education, work experience, academic background, and company size for respondents' demographic analyses. The last section was composed of 48 detailed questionnaires to understand the influencing factors in accepting AI-based technologies. Each question used a five-point Likert scale (ranging from "strongly disagree" to "strongly agree") to evaluate influencing factors on accepting AI-based technologies.

The survey carried out in South Korea sent a total of 500 surveys by e-mail from December 2022 to January 2023. Among the sent surveys, 432 responded, which showed an 86.4% response rate. Moreover, the same English-translated version was used for the British cases. Considering the differences in meaning and nuance that could occur while translating the survey, translation errors were minimized by assigning a translator who could speak both Korean and English, followed by having a native speaker proofread. The survey carried out in the UK sent a total of 200 surveys from mid-March to the end of April

2023; 143 surveys were returned, which showed a 71.5% return rate. A test for normality and outliers was conducted to measure variables on the surveys obtained from Korea and Britain. Through this process, a final effective sample of 420 and 123 questionnaires from Korea and the UK, respectively, was obtained and utilized for the data analysis.

A valid sample acquired through an e-mail survey was utilised for various empirical analyses, including hypothesis verification. On a preferential basis, frequency analysis and descriptive statistical analyses were conducted on all measurement variables in order to identify data input errors prior to verification. Through this process, error values were deleted, and the variables measured on a continuous interval scale were checked for normal distribution, skewness, and kurtosis to assess the normality of the measurement variables. The analysis content utilised after these procedures is as follows.

First, frequency analysis was conducted to examine the demographic information of the respondents. Secondly, descriptive statistical analysis was implemented to look into the basic traits (e.g., average, standard deviation, skewness, etc.) of continuous variables of constructs technology, personal competence, organisational competence, social influence, perceived usefulness, perceived ease of use, satisfaction of the technology, and firm size). Thirdly, reliability analysis (using Cronbach $\alpha$ coefficient) and Confirmatory Factor Analysis (CFA) was conducted to evaluate internal consistency, and measurement lists' convergent validity and construct validity of the construct. Lastly, research hypothesis verification through influencing relationships between constructs was analysed based on Structural Equation Modelling (SEM). In the research, IBM SPSS 28 and AMOS28 programs were utilised to verify the hypothesis on influencing factors in accepting AI-based technologies.

### *3.2. Research Model*

As the goal of the study is to identify the degree of AI-based technology acceptance in Korean and British construction industries, TAM by Davis was utilised [52]. Based on the research model suggested in previous studies, the research model presented this time [33,65,68,70,82–86] analysed the factors that affect usage intention and the acceptance of AI-based technologies in each country. As shown in Figure 4, based on the previous studies, the research model used in the study has set technology, individual, organisational, and social influences as the external influencing factors along with external variables that affect usage intention and usefulness.

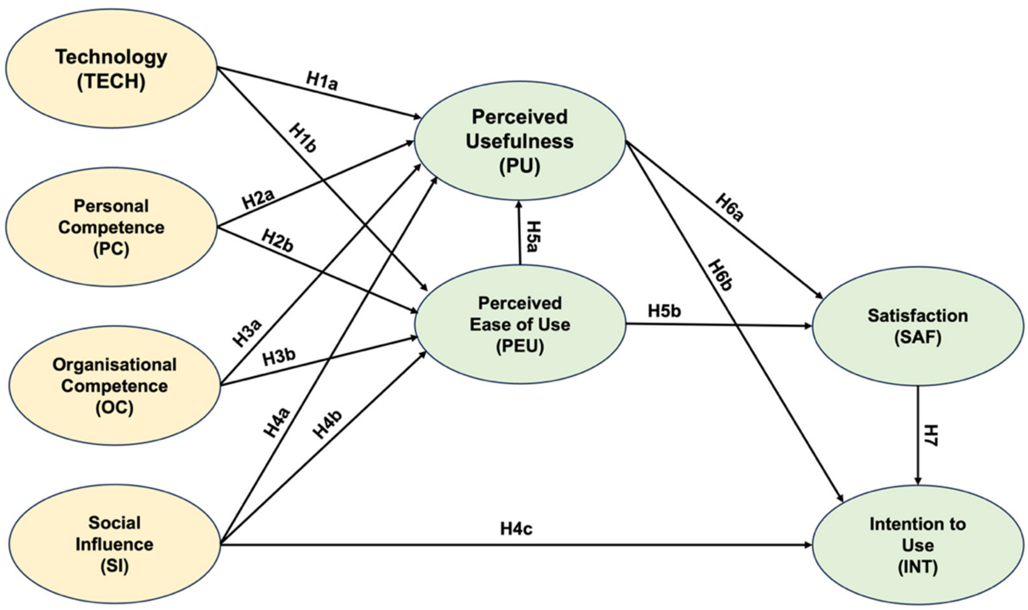


**Figure 4.** Research model.

Furthermore, technology usage satisfaction was added as a basic variable, along with perceived usefulness, perceived ease of use, and usage intention suggested in TAM. Together with these basic variables, based on the possibility that accepting new technology and individual competence may differ depending on the company size, the size of the company was regarded as a moderating variable. In addition, considering that an individual's experience may be able to affect perceived usefulness and perceived ease of use upon adopting and utilising new technology, experience was chosen as a moderating variable that influences perceived usefulness and perceived ease of use.

Based on TAM, the research analysed the relationship between the latent variables suggested, utilising the structural equation model. The structural equation model was utilised to set and verify the causal relationship between perceived usefulness, perceived ease of use and technological satisfaction, and the sizes of their influences, which affect usage intention used as the dependent variable. Table 1 describes each construct suggested by the research model.

**Table 1.** Individual constructs suggested from the research model.

| Construction | Description | Source |
| --- | --- | --- |
| Technology | • Technological factor shows technological suitability, ease of use, and compatibility in accepting AI-based technology or product.<br>• Compatibility is defined as the degree of correspondence to previous experience, work practice, system, and requirements of potential users.<br>• Although new AI-based technology could enhance work efficiency and act as a factor for enhancing competitive advantage, the organisation or the members may not select if it lacks compatibility. | [87–90] |
| Personal competence | • Users of new technology gain confidence in it by repeatedly utilising the information technology to perform tasks, and the confidence affects expected outcomes through information technology.<br>• Self-efficacy and individual innovativeness show the attitude towards encountering new technology, and an individual's positive impact affects perceived ease of use and usefulness when accepting new technology. | [82,86,90–93] |
| Organisational competence | • Members of the organisation are unwittingly affected by the organisational culture, and the organisational culture has an enormous impact on the attitude toward accepting new technology.<br>• Successful utilisation is a potential risk factor in accepting and using new technology and accommodating risk, and the degree of tolerance is useful in forming trust among the members of the organisation and affects on active adoption of new technology. | [67,94–99] |
| Social influence | • Social influence refers to the social environment that affects when an individual makes the decision, which indicates the related circumstances to support technology and the social atmosphere when accepting new technology. | [66,69,84,100,101] |
| Perceived ease of use | • Perceived ease of use refers to the degree of potential users' belief that using particular information technology or system would cost less physical or psychological trouble or the expectation that they will be able to utilize new technology or system without much effort. | [52,65,70,102] |
| Perceived usefulness | • Perceived usefulness refers to the user's judgment that the individual work performance capability or quality of life has been enhanced by utilising new technology or system compared to the previous system in use. | [52,54–57] |
| Satisfaction | • Satisfaction is defined as the information system user's perceptive and subjective evaluation based on the system quality being used. | [73,95,103–106] |

The Research hypothesis includes a comparison and analysis of the causal relationship and the size of perceived ease of use, perceived usefulness, technology satisfaction, and usage intention of construction industry workers that affect AI base technology intention for Korea and the UK. The study has added four external variables (technology, personal competence, organisational competence, and social influence) to TAM suggested by Davis [52] and has set a total of eight research hypotheses. Moreover, the size of the company was considered as a moderating variable based on the possibility that the attitude towards accepting new technologies may differ due to company size, together with these basic variables [48]. The research hypotheses were set as follows.

**Hypothesis 1.** *Technological trait affects user's perceived usefulness and perceived ease of use when introducing AI-based technologies and products*.

**Hypothesis 2.** *Personal competence affects user's perceived usefulness and perceived ease of use when introducing AI-based technologies and products*.

**Hypothesis 3.** *Organisational competence affects user's perceived usefulness and perceived ease of use when introducing AI-based technologies and products*.

**Hypothesis 4.** *Social influence affects user's perceived usefulness and perceived ease of use when introducing AI-based technologies and products*.

**Hypothesis 5.** *Perceived usefulness affects user satisfaction with technology and usage intention when introducing AI-based technologies and products*.

**Hypothesis 6.** *Perceived ease of use affects user satisfaction with technology and perceived usefulness when introducing AI-based technologies and products*.

**Hypothesis 7.** *Satisfaction with technology affects user's usage intention when introducing AI-based technologies and products*.

**Hypothesis 8.** *The size of the company affects from hypotheses one to seven when introducing AI-based technologies and products*.

## 4. Results and Data Analysis

### *4.1. Technological Statistics*

The result of the technological statistics of the survey respondents is as in Table 2. The respondents of the study were a total of 575, 432, and 143 from Korea and the UK. For Korea, male and female respondents were 315 and 105, respectively, which appear to form 75% and 25% of the gender ratio. Furthermore, in terms of the distribution by age group, respondents aged 28 or older and under 36 accounted for 157 individuals, representing the highest proportion at approximately 37.4%. Next, respondents aged 36 or older and under 44 accounted for 107 individuals, representing 25.5% of the total respondents. Additionally, there were 76 respondents aged 44 or older and under 52, making up 18.1% of the total, while respondents aged 20 or older and under 28 accounted for 37 individuals, representing 16.0% of the total respondents. In the case of the UK, respondents aged 36 or older and under 43 constituted 56 individuals, representing the highest age group distribution at 40% of the total. Following this, respondents aged 19 or older and under 27, and those aged 44 or older and under 51, accounted for 27 and 25 individuals, respectively, making up 19.30% and 17.90% of the total, respectively.

**Table 2.** Demographic analysis.

| Demographic Variables | Categories | South Korea | | United Kingdom | |
|---|---|---|---|---|---|
| | | Frequency | Percentage | Frequency | Percentage |
| Gender | Female | 105 | 25.0 | 48 | 34.3 |
| | Male | 315 | 75.0 | 92 | 65.7 |
| Age | 19~27 | 37 | 16.0 | 27 | 19.3 |
| | 28~35 | 157 | 37.4 | 16 | 11.4 |
| | 36~43 | 107 | 25.5 | 56 | 40.0 |
| | 44~51 | 76 | 18.1 | 25 | 17.9 |
| | 52~59 | 12 | 2.9 | 7 | 5.0 |
| | Above 60 | 1 | 0.2 | 9 | 6.4 |
| Education | High school and below | 0 | 0 | 11 | 7.9 |
| | Bachelor's degree | 246 | 58.6 | 89 | 63.6 |
| | Master's degree | 154 | 36.7 | 30 | 21.4 |
| | Doctorate and above | 20 | 4.8 | 10 | 7.1 |
| Type of company | Construction management | 210 | 50.0 | 77 | 55.0 |
| | Architecture and interior design | 76 | 18.1 | 25 | 17.9 |
| | Architectural structure design | 118 | 28.1 | 12 | 8.6 |
| | Building maintenance and operation | 8 | 1.9 | 7 | 5.0 |
| | Research and development | 8 | 1.9 | 11 | 7.9 |

In terms of industrial distribution of the research survey respondents, the ratio of workers in the construction field showed to be the highest in both Korea and the UK. Moreover, it was identified that respondents working in designing or structural designing made up a high portion in both countries. As a result of research on the age and education level of respondents, it appeared to be the same in Korea and the UK. Both countries had the highest distribution of bachelor's degrees. A total of 246 and 89 had bachelor's degrees among the respondents in Korea and the UK, making up 58.6% and 63.6%.

There were no big differences regarding cognizance of AI-related technology among Korean and British construction industry workers. The average cognizance of AI-related technology was between 2.7 points and 3.6 points in both countries, which was the middle standard, but Korean construction industry workers scored 3.3 points, which was slightly higher than that of the British, at 3.1 points. Taking a look into response results per TAM measurement variable, it was identified that construction industry workers in Korea were relatively amicable and showed positive likability towards new products or technologies and had a higher willingness to utilise them if they had opportunities. This is considered due to the industrial trait that is centred on manufacturing business to produce products with new technologies or goods applied, and that the new product has a relatively lower price based on this. On the other hand, construction industry workers in the UK were shown to be less influenced on such as overall industry's movement or social flow when adopting new technologies or products. Additionally, construction industry workers in Korea showed to be highly influenced by the satisfaction that comes from using technology, compared to those in the UK.

### *4.2. Model Validation*

The research assessed validation on eight constructs (TECH, PC, OC, SI, PEU, PU, SAF, and IU) and 48 measurement items that form these. To assess the overall suitability of the research model, the ratio of $x^2$ to a degree of freedom ($df$), root-mean-square residual (RMR), goodness-of-fit (GIF), comparative fit index (CFI), Bentler and Bonnet's Normed Fit Index (NFI), and Tacker–Lewis index (TLI) were utilised as model validation measurement index [107]. Regarding the model validation assessed in the study, $x^2/df$, RMR, NFI, TLI, and CFI indexes for Korea were over than the suggested fiducial value except for GFI, and the UK showed higher model validation estimate index value than the suggested (Table 3). On the other hand, the GFI for Korea was 0.843, which did not meet the suggested level of over 0.9, but is considered relatively fine to be over 0.8 according to the research result by

Gefen, Straub and Boudreau [108]. Thus, the estimate model validation of Korea and the UK studied in the research is shown to be appropriate to a significant level.

**Table 3.** Research model validation estimate index results.

| Indices | Threshold | Measurement Model | |
|---|---|---|---|
| | | South Korea | United Kingdom |
| $X^2$/df | ≤3.0 | 2.282 | 2.674 |
| RMR | ≤0.1 | 0.040 | 0.052 |
| GIF | ≥0.9 | 0.843 | 0.814 |
| NFI | ≥0.9 | 0.905 | 0.911 |
| TLI (NNFI) | ≥0.9 | 0.930 | 0.942 |
| CFI | ≥0.9 | 0.944 | 0.980 |

Furthermore, the study examined how precisely and properly measurement variables of the construct were estimated by implementing confirmatory factor analysis on individual constructs (Table 4). Confirmatory factor analysis evaluates the conformity of the measurement model by estimating the relationship between measurement factors and constructs [108]. Among the confirmatory factor analysis, Cronbach's $\alpha$ is the criterion showing whether the observed variables such as survey questionnaires used to estimate constructs, have internal consistency, and are utilised for checking the credibility of the constructs [107,109]. In general, if Cronbach's $\alpha$ is over 0.7 and less than 0.8, the internal consistency of the observed variables is considered satisfactory. Moreover, if the value is between 0.8 and 0.9, it is regarded as good, and excellent if over 0.9. Table 4 shows Cronbach's $\alpha$ derived from the measurement model to check the credibility between the constructs for the study. For Korea and the UK, Cronbach's $\alpha$ was identified to be between 0.869 and 0.943 and 0.800 and 0.940 each.

The average variance extracted (AVE) and composite reliability (CR) values are used for deciding convergence validity by comparing each threshold value. AVE values indicate how well the measurement factors that measure constructs explain, and convergence validity is proven in general when over 0.5. Moreover, CR value is used for measuring construct reliability by taking the correlation between measurement factors into consideration, and convergence validity is known to be proven when over 0.7 generally. Once these values meet the threshold value, the convergence validity of the construct could be identified [107]. Table 4 presents the AVE and CR values of the measurement model, and the values for Korea and the UK exceeded 0.5 and 0.7 each, which identified convergence validity. These results indicate that measurement factors have enough consistency and credibility among the constructs forming the suggested research model and meet the convergence validity of the model.

It is an important step to check discriminant validity in evaluating the measurement tool or effectiveness of the model, and the correlation matrix of Korean and British constructs are as shown in Tables 5 and 6. If the constructs are indistinguishable, there may be problems occurring in the credibility and validity of measurement tools or models and may obtain distorted results. Thus, the research aims to identify differentiation degrees among constructs through appropriate methods so as to meet discriminant validity. Discriminant validity is a notion of evaluating the degree of differentiation of constructs within the measurement tool or model. This shows that the constructs measure different notions. In other words, this means that once discriminant validity is met, a construct is measured independently, regardless of other constructs. Generally, discriminant validity is identified based on AVE and is considered to meet discriminant validity if the AVE value is bigger than the squared value of the correlation coefficient of the construct, that is, squared correlation. Namely, it is to evaluate whether the constructs have enough independence in measuring different traits. As shown in Tables 5 and 6, the Korean and British latent variable's square root values of average variance extracted were measured higher than the correlation values of others. These results show that the research model suggested in the study has discriminant validity.

**Table 4.** The result of confirmatory factor analysis on measurement model.

| Construct | Measurement | Factor Loading | | Cronbach's α | | AVE | | CR | |
|---|---|---|---|---|---|---|---|---|---|
| | | KR | UK | KR | UK | KR | UK | KR | UK |
| Technology (TECH) | TECH1 | 0.789 | 0.770 | 0.908 | 0.911 | 0.692 | 0.783 | 0.931 | 0.818 |
| | TECH2 | 0.846 | 0.704 | | | | | | |
| | TECH3 | 0.870 | 0.801 | | | | | | |
| | TECH4 | 0.799 | 0.717 | | | | | | |
| | TECH5 | 0.761 | 0.703 | | | | | | |
| | TECH6 | 0.735 | 0.721 | | | | | | |
| Personal Competence (PC) | PC1 | 0.767 | 0.825 | 0.873 | 0.800 | 0.529 | 0.623 | 0.870 | 0.754 |
| | PC2 | 0.731 | 0.806 | | | | | | |
| | PC3 | 0.762 | 0.808 | | | | | | |
| | PC4 | 0.610 | 0.756 | | | | | | |
| | PC5 | 0.641 | 0.729 | | | | | | |
| | PC6 | 0.645 | 0.753 | | | | | | |
| Organisational Competence (OC) | OC1 | 0.900 | 0.862 | 0.869 | 0.842 | 0.654 | 0.577 | 0.944 | 0.861 |
| | OC2 | 0.922 | 0.850 | | | | | | |
| | OC3 | 0.895 | 0.869 | | | | | | |
| | OC4 | 0.917 | 0.857 | | | | | | |
| | OC5 | 0.908 | 0.816 | | | | | | |
| | OC6 | 0.923 | 0.800 | | | | | | |
| | OC7 | 0.941 | 0.896 | | | | | | |
| | OC8 | 0.656 | 0.863 | | | | | | |
| | OC9 | 0.923 | 0.874 | | | | | | |
| Social Influence (SI) | SI1 | 0.735 | 0.801 | 0.903 | 0.861 | 0.638 | 0.610 | 0.913 | 0.808 |
| | SI2 | 0.656 | 0.774 | | | | | | |
| | SI3 | 0.741 | 0.748 | | | | | | |
| | SI4 | 0.704 | 0.736 | | | | | | |
| | SI5 | 0.772 | 0.714 | | | | | | |
| | SI6 | 0.765 | 0.762 | | | | | | |
| Perceived Ease of Use (PEU) | PEU1 | 0.818 | 0.788 | 0.943 | 0.808 | 0.779 | 0.677 | 0.948 | 0.861 |
| | PEU2 | 0.817 | 0.744 | | | | | | |
| | PEU3 | 0.860 | 0.704 | | | | | | |
| | PEU4 | 0.851 | 0.768 | | | | | | |
| | PEU5 | 0.888 | 0.792 | | | | | | |
| | PEU6 | 0.831 | 0.774 | | | | | | |
| Perceived Usefulness (PU) | PU1 | 0.844 | 0.768 | 0.934 | 0.840 | 0.753 | 0.676 | 0.946 | 0.893 |
| | PU2 | 0.865 | 0.881 | | | | | | |
| | PU3 | 0.863 | 0.820 | | | | | | |
| | PU4 | 0.882 | 0.816 | | | | | | |
| | PU5 | 0.859 | 0.847 | | | | | | |
| Satisfaction (SAF) | SAF1 | 0.819 | 0.952 | 0.932 | 0.940 | 0.739 | 0.840 | 0.919 | 0.904 |
| | SAF2 | 0.796 | 0.914 | | | | | | |
| | SAF3 | 0.822 | 0.816 | | | | | | |
| | SAF4 | 0.852 | 0.820 | | | | | | |
| Intention to Use (INT) | INT1 | 0.810 | 0.875 | 0.912 | 0.854 | 0.652 | 0.774 | 0.916 | 0.911 |
| | INT2 | 0.795 | 0.872 | | | | | | |
| | INT3 | 0.847 | 0.892 | | | | | | |
| | INT4 | 0.873 | 0.875 | | | | | | |
| | INT5 | 0.587 | 0.883 | | | | | | |
| | INT6 | 0.568 | 0.878 | | | | | | |

Note: KR = South Korea; UK = United Kingdom; AVE = Average Variance Extracted and CR = Composite Reliability.

**Table 5.** Correlation matrix for constructs (South Korea).

| | TECH | PC | OC | SI | PEU | PU | SAF | INT |
|---|---|---|---|---|---|---|---|---|
| **TECH** | 0.832 | | | | | | | |
| **PC** | 0.693 | 0.727 | | | | | | |
| **OC** | 0.731 | 0.552 | 0.808 | | | | | |
| **SI** | 0.809 | 0.676 | 0.687 | 0.799 | | | | |
| **PEU** | 0.555 | 0.775 | 0.549 | 0.653 | 0.868 | | | |
| **PU** | 0.724 | 0.751 | 0.691 | 0.737 | 0.827 | 0.883 | | |
| **SAF** | 0.711 | 0.692 | 0.731 | 0.756 | 0.760 | 0.925 | 0.859 | |
| **INT** | 0.208 | 0.155 | 0.307 | 0.213 | 0.150 | 0.182 | 0.207 | 0.807 |

**Table 6.** Correlation matrix for constructs (UK).

| | TECH | PC | OC | SI | PEU | PU | SAF | INT |
|---|---|---|---|---|---|---|---|---|
| **TECH** | 0.762 | | | | | | | |
| **PC** | 0.574 | 0.794 | | | | | | |
| **OC** | 0.687 | 0.592 | 0.769 | | | | | |
| **SI** | 0.794 | 0.184 | 0.447 | 0.874 | | | | |
| **PEU** | 0.487 | 0.372 | 0.317 | 0.274 | 0.789 | | | |
| **PU** | 0.814 | 0.328 | 0.587 | 0.321 | 0.138 | 0.827 | | |
| **SAF** | 0.547 | 0.477 | 0.479 | 0.324 | 0.293 | 0.694 | 0.922 | |
| **INT** | 0.561 | 0.368 | 0.412 | 0.307 | 0.387 | 0.544 | 0.778 | 0.884 |

### *4.3. Verification of Structural Equation Modelling*

After implementing the confirmatory factor analysis presented in the previous clause, an analysis of structural equation modelling was performed to verify the research hypothesis. Structural Equation Modelling (SEM) is a statistical methodology that models and analyses complex relationships between diverse variables. The SEM is a method to analyse data by simultaneously considering relationships between the observed variables and latent variables (or constructs), which is able to evaluate causal relationships and correlations between many variables at the same time. SEM includes various methods such as path analysis, regression analysis, factor analysis, latent growth modelling, and latent variable mixture modelling, and is one of the widely used multivariate statistics techniques, which is able to effectively model and understand the relationship between complex structures and variables through these.

The selection of hypothesis on structural equation was set and decided if CR (t value) was over $\pm 1.96$, and significance level of under 0.05. Prior to verifying the causal relationship, the overall conformity of the Korean model was identified to all meet fiducial values, with which the study's theoretical model was compatible. Moreover, the standardised coefficient's $p$-value was utilised to explain the relationship between the constructs within the model. Paths with $p$-values greater than 0.05 were considered statistically insignificant; thus, these paths were removed. The path results for the Korean case were derived as shown in Table 7, and the PC-PU path, SI-PU path, and SI-INT path were removed from the model due to $p$-values exceeding 0.05. Similarly, for the UK case, the path results were presented in Table 8, and the TECH-PEU path, PC-PEU path, and SI-PU path were removed from the model as their $p$-values exceeded 0.05.

Furthermore, path analysis was performed to evaluate the causal relationship between the variables and to build the model. Path analysis is a method helpful in visualising and understanding complicated interactions between diverse variables. Based on the observed variables, path analysis statistically evaluates the relationship between them and is able to assess the effectiveness and explanation ability of the model.

**Table 7.** Influencing relationship verification results on theoretical model of SEM (South Korea).

| Hypotheses | Relationship | | | β | SE | CR | ρ | Results |
|---|---|---|---|---|---|---|---|---|
| H1a | PU | ← | TECH | 0.268 | 0.047 | 5.753 | *** | Supported |
| H1b | PEU | ← | TECH | 0.576 | 0.085 | 5.418 | *** | Supported |
| H2a | PU | ← | PC | 0.059 | 0.043 | 1.380 | 0.168 | Not supported |
| H2b | PEU | ← | PC | 0.564 | 0.046 | 12.157 | *** | Supported |
| H3a | PU | ← | OC | 0.084 | 0.025 | 3.338 | *** | Supported |
| H3b | PEU | ← | OC | 0.124 | 0.031 | 5.000 | *** | Supported |
| H4a | PU | ← | SI | 0.073 | 0.047 | 1.551 | 0.121 | Not supported |
| H4b | PEU | ← | SI | 0.290 | 0.058 | 5.000 | *** | Supported |
| H4c | INT | ← | SI | 0.014 | 0.077 | 0.187 | 0.851 | Not supported |
| H5a | PU | ← | PEU | 0.485 | 0.039 | 12.574 | *** | Supported |
| H5b | SAF | ← | PEU | 0.135 | 0.038 | 3.563 | *** | Supported |
| H6a | SAF | ← | PU | 0.680 | 0.039 | 17.563 | *** | Supported |
| H6b | INT | ← | PU | 0.333 | 0.072 | 4.030 | *** | Supported |
| H7 | INT | ← | SAF | 0.106 | 0.075 | 1.409 | ** | Supported |

Note: β = Standardised Regression Coefficient; SE = Standardised Error and CR = Critical Ratio (t-value), *** $p < 0.001$, ** $p < 0.05$.

**Table 8.** Influencing relationship verification results on theoretical model of SEM (UK).

| Hypotheses | Relationship | | | β | SE | CR | ρ | Results |
|---|---|---|---|---|---|---|---|---|
| H1a | PU | ← | TECH | 0.354 | | 3.477 | *** | Supported |
| H1b | PEU | ← | TECH | 0.047 | | 0.699 | 0.203 | Not supported |
| H2a | PU | ← | PC | 0.399 | | 4.057 | ** | Supported |
| H2b | PEU | ← | PC | 0.109 | | 0.908 | 0.380 | Not supported |
| H3a | PU | ← | OC | 0.142 | | 2.037 | *** | Supported |
| H3b | PEU | ← | OC | 0.338 | | 2.414 | *** | Supported |
| H4a | PU | ← | SI | 0.041 | | 0.443 | 0.677 | Not supported |
| H4b | PEU | ← | SI | 0.244 | | 5.474 | *** | Supported |
| H4c | INT | ← | SI | 0.644 | | 5.784 | ** | Supported |
| H5a | PU | ← | PEU | 0.266 | | 3.647 | *** | Supported |
| H5b | SAF | ← | PEU | 0.413 | | 4.719 | *** | Supported |
| H6a | SAF | ← | PU | 0.513 | | 6.251 | *** | Supported |
| H6b | INT | ← | PU | 0.414 | | 4.144 | *** | Supported |
| H7 | INT | ← | SAF | 0.651 | | 3.675 | ** | Supported |

Note: β = Standardised Regression Coefficient; SE = Standardised Error and CR = Critical Ratio (t-value), *** $p < 0.001$, ** $p < 0.05$.

Analysing the outcomes of the path analysis conducted in the context of Korea, as depicted in Figure 5, it becomes evident that both technological and organisational variables exert a significant impact on perceived usefulness and personal competence. Similarly, it is discerned that perceived ease of use is influenced by a combination of technological, organisational, and social factors. In the case of construction industry workers in Korea, acknowledging the usefulness of AI-based technologies is the case when these technologies have high compatibility with the existing ones or their companies or organisations are trying to utilize them. Because of the trait that many stakeholders participate in construction projects, this is considered due to the importance of compatibility with the previous product and seamless flow when adopting new technologies or products. In addition, the reason that not only technological compatibility and organisational factor but also personal competence is influential in utilising AI-based technology is considered due to enhancing task performance as well as manifestation of self-efficacy, which is presented as a new technology or product.

Upon scrutinising the outcomes derived from the path analysis conducted in the United Kingdom, as illustrated in Figure 6, a notable observation is made: the organisational factor emerges as a determinant that exerts influence on perceived usefulness, in conjunction with the technological factor and personal competence. Moreover, perceived ease of use could be regarded to be influenced by organisational competence and social factors. For the case of construction industry workers in the UK, personal competence was identified to affect perceived usefulness, which is different from Korea's case. This is considered to result from distinct cultural differences due to individualistic traits, unlike the Korean construction organisation where collectivist sentiments are dominant [77]. However, it was analysed that technological factors had a negative (-) impact on perceived ease of use, which is due to the trait that sufficient verification and usage result are based upon utilising new technology or product.

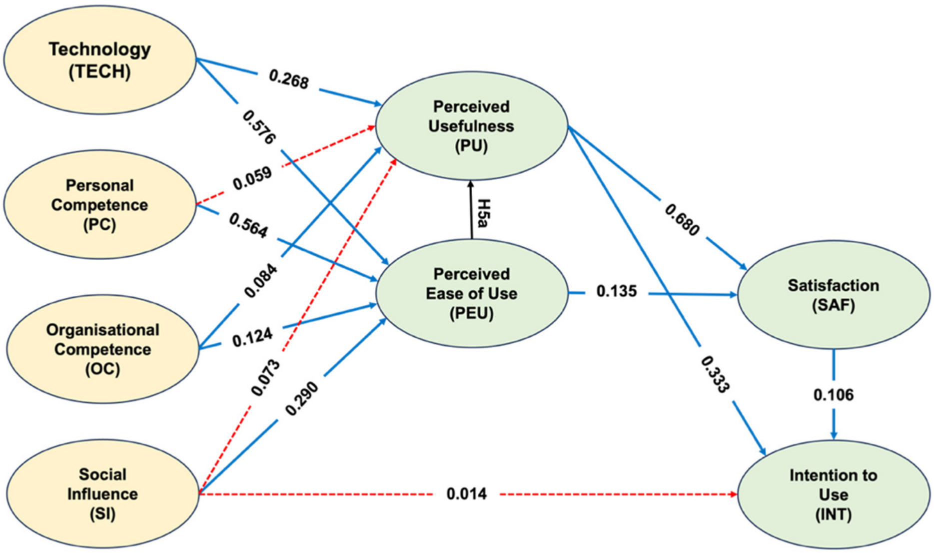


**Figure 5.** Test of the research model for South Korea (Red lines are referring to "Not supported" result from Table 7).

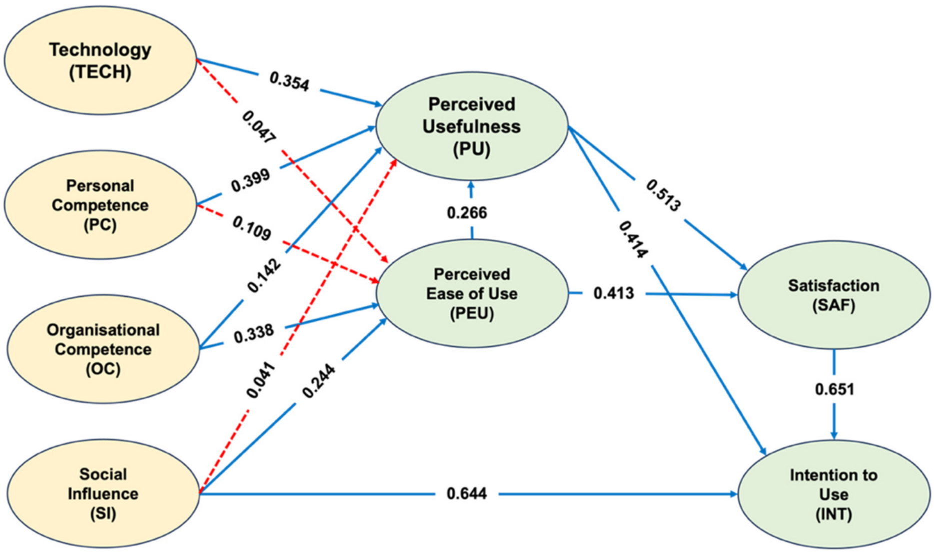


**Figure 6.** Test of the research model for the United Kingdom (Red lines are referring to "Not supported" result from Table 8).

## 5. Discussion and Implications

### *5.1. Comparison between South Korea and the United Kingdom Cases*

The research showed commonalities and differences between South Korean and British workers in the construction industry in accepting AI-based technologies. Perceived usefulness having a positive (+) influence over technology satisfaction and usage intention was a common point. In particular, technological factors and organisational competence were points for positive (+) impact in both countries. In the technological aspect, it was identified that technological compatibility was an important factor in choosing or selecting AI-based technologies, which is the research target. The construction industry has less innovativeness and low labour productivity compared to the others, are shown in a variety of research and reports [26,50,71,110,111], and these tendencies seem to result in labour-intensive traits as well as the conservativeness against new technologies, and the research considers these traits appear when accepting AI-based technologies [112–114].

Furthermore, given the substantial temporal investment required from project initiation to completion, owing to the inherent attributes of construction projects, a distinct inclination towards precision and conservatism becomes apparent when embracing novel technologies or products. Consequently, a discernible proclivity exists for the adoption of products that have undergone comprehensive validation and attained a state of stability, particularly when introducing technologies or products founded on artificial intelligence within the construction sector. This inclination was observed in both nations, underscoring the essential nature of a prerequisite verification process preceding any form of acceptance.

Furthermore, organisational competence, which is influenced by perceived usefulness, refers to those that involuntarily affect the members of the organisation, such as organisational culture and building trust among the members [115–118]. In particular, the construction industry or construction project is executed through the mutual cooperation of many stakeholders or different organisations than that of individuals. Due to this tendency of collective task execution, an individual that belongs to a group has influence over the adoption or usage of new technologies or products with factors such as organisational culture or communication system. AI-based products or technologies are not just simple new ones but technological changes that will bring paradigm transition of new communication systems or work methods. Therefore, product selection is considered a total change of the organisation rather than a simple individual's volition or preference. Besides, in terms of AI-based products or technologies, since accommodation as a whole company or top-down selection and operation are important for AI-based products or technologies, organisational competence was examined to be an important influencing factor in both Korea and the UK.

Next, as shown in Figures 5 and 6, perceived ease of use was analysed to have a positive (+) impact on perceived usefulness and satisfaction in both Korea and the UK. The external variables that influenced perceived ease of use in both countries were identified as organisational competence and social factors. Similar to perceived usefulness, whether to accept AI-based products or technologies depended on the goals or interests of an organisation rather than individual desire or craving. Particularly, individuals within an organisation, as members, are considered to be influenced by factors such as ease of use in the adoption of AI-based products or technologies.

Perceived ease of use was identified to be influenced not only by the organisation but also by the bigger external group, namely society (Figures 5 and 6). In particular, as a pivotal industry of a country, construction is an important industry that makes up 20% of gross domestic product and 6% globally [19]. Due to these roles, the construction field is largely influenced by the external environment as an industry. Recently, governments from various countries have been devoted to funding and training human resources to foster the fourth Industrial Revolution-based technologies [119]. Korea and the UK, the research targets, are also trying in many ways to keep pace with these flows and to play leading roles [120]. ChatGPT, presented in the industry in the second half of 2022, is providing not only the previous image-based AI technology development but also new possibilities based on large language models (LLM) and transformers [121,122]. In the adoption of AI-based technologies in the construction industry, the influence goes beyond the organisational influence of each company and extends to the collective group or even larger national trends, which the company is unable to defy. Amidst such dynamics, the construction industry also considers social influence as an important factor affecting the perceived ease of use in adopting and choosing AI-based technologies.

Technology satisfaction was analysed to be an influencing factor on usage intention in Korea and the UK. Especially in a group with strong conservatism, the satisfaction of the users is an important factor in enhancing technological efficacy in adopting and utilising different technologies or products than the previous ones. Efficacy is expressed into satisfaction in a moment, and it was identified through the study that satisfaction played an important influencing factor in technology adoption and proliferation. However, conservativeness in the construction industry does not mean to reject acquiring new technologies or innovation. The conservativeness in the construction industry results from the industrial traits, which are long-term projects, and a large number of participants and stakeholders; thus, is considered to refer to precision and enough reviewing prior to adopting new technologies.

The sharp differences in adopting AI-based technologies from Korean and British work in the construction industry analysed in the study were personal competence and social influence. For Korea, personal competence had a positive impact (+) on perceived ease of use, whereas, for the UK, it had a positive impact (+) on both perceived ease of use and perceived usefulness. Personal competence is one of the factors for an individual to gain confidence in information and communication technology or new technology through work, and to influence task performance or potential utilisation [83,85,123]. In the case of Korea, the country is playing the role of production base for various information and communication products. The country has a rapid period of launching new products and replacing them, and these social and industrial tendencies are identified to influence individuals to adopt and utilize new products [124]. However, it was identified that apart from personal tendencies, individuals within the organisation mostly were affected by the organisation or their company, and this is considered due to Korean organisational culture, which is reluctant to reveal personal traits in companies or organisations [77,98,99].

Furthermore, differences between Korea's and the UK's social influence affecting the usage intention of AI-based products or technologies were shown in the study. In Eastern culture, it is known that individuals act accordingly and are restrained by social norms, influences, or standards since collectivism is strong [125–127]. However, as a result of the study, it was analysed that workers in the Korean construction industry are not affected by the social atmosphere or flow when selecting or utilising AI-based products or technologies. On the other hand, unlike the Korean case, the workers in the British construction industry appeared to be influenced by the social atmosphere regarding the usage intention of AI-based products or technologies. The results come from a liberalistic economic system and openness, social, and environmental factors shown in Western countries, and are considered to be reflected intact within the construction industry upon adopting AI-based technologies.

### *5.2. Implications*

The research is able to draw the following implications. First, it was identified that consideration of technological traits such as technological compatibility is an important factor to construction industry workers in Korea and the UK when adopting and utilising AI-based technologies to work. When considering technological attributes, it is deemed that the evaluation of adopting AI-based technologies, expanded from the technologies currently utilised within the organisation, should precede the introduction of AI-based technologies or products. Moreover, considering the trait that the construction industry is labour intensive, it should be evaluated not only on the corporate level but also laborers', on which technology would be applicable. Next, it is the reality that the construction industry is left behind than others in terms of technological innovation and labour productivity [128]. These facts refer to many possibilities of technological innovation application and especially imply that AI technologies have higher probabilities of solving on-site problems, such as safety accidents, to prevent human errors. Together with these practical implications, research on cross-cultural aspects is expected to fulfil insufficient parts in the construction industry when studies on adopting new technologies or products through the application of existing technological models are conducted. In particular, at this point where the sizes of international projects performed together by technicians or workers from various cultures are getting bigger, the factors to accepting technology, identified through the study, are presenting academic implications to be reviewed prior to adopting AI-based technologies.

### *5.3. Limitations and Future Research*

Although the research has conducted analysis on factors that influence accepting AI-based technologies with Korean and British construction industry workers as targets, it is considered that there are following limitations and necessities to be studied further. First, the survey was conducted on 432 and 143 people with various businesses within the Korean and British construction industry so as to verify the research model. However, the collected data had limits to generalising the usage intention of members within the Korean and British construction industry towards AI-based technology or products. Moreover, since potential users' attitudes or intentions may change depending on the degree of technological advancement and innovation, analyses of long-term trends, transition aspects, and usage intention are considered necessary rather than doing research as a one-time event.

Furthermore, the research has conducted a survey on individuals in various businesses within the construction industry as one study target. However, the demographic analysis shown in Table 2 indicates that there are various businesses in the construction industry. Each business performs different works in the construction industry, and these differences may result in distinctions in utilisation, usage intention, and attitudes toward AI-based technologies or products. Thus, it seems additional research on influencing factors of AI-based technology or products depending on industrial attributes within the construction industry, where diversity exists, is necessary. Lastly, as recent construction projects are internationalised as well as being large-scale and complicated, stakeholders with diverse cultural backgrounds get to participate. As the project tends to show large-scale and complex tendencies, the attitudes toward accepting new or innovative technologies, such as AI-based ones, are considered to be different. Thus, additional research considering the project scale seems necessary as well.

## 6. Conclusions

The purpose of this study is to conduct an empirical analysis of the determinants that influence the acceptance of AI-based technologies or products among workers within the construction industries of South Korea and the United Kingdom. To achieve the stated research goal, this study employed a survey-based approach to analyse the key factors that contribute to the acceptance of AI-based technologies or products within the construction industries of South Korea and the United Kingdom. The research framework was constructed around the Technology Acceptance Model (TAM) initially proposed by Davis, which was supplemented by insights from relevant literature and input from expert interviews. The external variables considered in the analysis included technology attributes, personal competence, organisational competence, and social influence. These variables were chosen to comprehensively investigate the determinants influencing AI technology acceptance in the two aforementioned countries. As a result of the path analysis of the research model, perceived ease of use and perceived usefulness affected usage satisfaction in both countries and were identified to influence usage intention in the end. On the other hand, influences from external variables on perceived ease of use and perceived usefulness showed differences to a certain degree in South Korea and the UK. Construction industry workers in South Korea and Britain have perceived that technology and organisational competence influenced perceived usefulness. Moreover, the research result analysed that technology or product in South Korea and the UK, resulting from Eastern and Western cultural differences, is considered to play an important role in the cross-cultural study within the construction industry. Organisational competence and social influence were the common factors affecting perceived ease of use. This study holds particular significance within the realm of cross-cultural research in the construction industry. It undertakes an analysis of the factors that impact the assimilation of AI-driven technologies or products, specifically drawing from the cultural distinctions between two nations: South Korea and the UK, emblematic of Eastern and Western cultural paradigms, respectively.

**Author Contributions:** Conceptualisation, S.N. and S.W.W.; methodology, S.N.; software, S.N. and S.H.; validation, S.H. and S.W.W. and W.C.; formal analysis, S.N. and S.H.; investigation, S.H.; resources, S.N. and S.W.W.; data curation, S.N. and W.C.; writing—original draft preparation, S.N.; writing—review and editing, S.H.; visualisation, W.C.; supervision, C.K.; project administration, S.N.; funding acquisition, C.K. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the Korea Agency for Infrastructure Technology Advancement (KAIA) grant funded by the Ministry of Land, Infrastructure and Transport (Grant 1615012983) and the National Research Foundation of Korea (NRF) grant funded by the Korean government (MIST) (No. 2022R1I1A1A01053268).

**Data Availability Statement:** The data used to support the research are included within the article. In addition, some of the data in this study are supported by the references mentioned in the article. If you have any queries in terms of the data, they would be available from the correspondence upon request.

**Conflicts of Interest:** The authors declare no conflict of interest.

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