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Firm Size and Artificial Intelligence (AI)-Based Technology Adoption: The Role of Corporate Size in South Korean Construction Companies

Seunguk Na , Seokjae Heo *, Wonjun Choi, Sehee Han and Cheekyung Kim

Department of Architectural Engineering, College of Engineering, Dankook University, 152 Jukjeon-ro, Yongin-si 16890, Gyeonggi-do, Republic of Korea
* Correspondence: mill@dankook.ac.kr; Tel.: +82-31-8005-3727

Abstract: This research addresses the factors that impact the acceptance of AI-based technologies or products depending upon firm size in the construction industry, in which various corporates exist. In order to achieve the research goals, a technology acceptance model was applied to investigate the influencing factors in respect to adopting AI-based technologies or products. From the research results, technological and organizational factors were found to positively influence perceived usefulness and perceived ease of use. Corporate users perceived that technology is useful to their work and is easy to use when enough capital and education were invested prior to the company adopting AI-based technologies or products. It was found that perceived ease of use and perceived usefulness indicate satisfaction with new technology, and the higher the intention to use, the higher the satisfaction. In addition, as various information sharing and distribution channels increase, the frequency of use of new technologies or products also increases, not through traditional marketing, but through viral marketing via social media or promotion by influential persons or organizations. Furthermore, there are differences in the adoption of AI-based technologies or products depending on the size of the company.

Keywords: technology acceptance model; artificial intelligence; construction industry; firm size; mediating effect

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1. Introduction

In the middle of the 20th century, Alan Turing raised the question, "Can machines think?" [1]. In March 2016, half a century later, human beings realized that AI had come close to equaling us through the match between Google's AI Go program, 'AlphaGo', and Sedol Lee, professional ninth dan Go player, in Korea [2,3]. Later, AI became the main technology that could transform industrial processes through all parts of industry. The construction industry is also trying to develop as a new AI-based industry. Following this trend, terms including robot, unmanned aerial vehicle (UAV) or drone, digital twin, building information modeling (BIM), machine-learning, AI, and metaverse are now common in the construction industry [4–8].

The emergence of new products or services due to these technological advances has not always been welcomed. The introduction of the weaving machine in the early 19th century in Britain sparked the Luddite movement, a machine-destroying movement, due to the belief that weaving machines would reduce employment opportunities for workers [9]. Similarly, in many countries in the 21st century, including Korea, there have been conflicts with existing technology or dominant powers within the industry whenever a new fourth-industrial-revolution-based service or technology appears [10–12]. For instance, Uber, which emerged as a new transport intermediary platform service, raised a dispute by directly conflicting between its purpose of "carrying people for monetary exchange" and the taxi-related laws of each country [10]. In addition, ChatGPT and illustration using artificial intelligence, which appeared in early 2023, pose a threat to jobs in existing occupations, such as reporting, writing, or illustration, and have created friction as a result [13].

Although there are confrontations and conflicts between existing and new technologies every time a new technology appears, humanity eventually accepts and utilizes the new technology. AI or machine-learning, the main technologies of the fourth industrial revolution, are used in various fields and are transforming our lives and industries [14–17]. The construction industry, which requires mass manpower, capital, and resources, is considered a traditional industry that plays a crucial role in the national economy. However, compared with many industries, digital transformation in the construction industry is a slow process [18–20]. At a point where the outcome from applying AI-based technologies or products is becoming clearer in various industrial fields, the awareness that the construction industry should not be left behind is spreading [5,7,20–22]. Singapore launched the Building and Construction Authority (BCA)'s Construction Industry Transformation Map in 2017. Through fourth industrial revolution technology, they are enhancing productivity, reducing expenses and safety accidents, and creating job opportunities in the construction industry [23]. Similarly, Germany and the UK are pursuing cost reduction and productivity advancement by utilizing digital technology, through "Construction Site 4.0" and "Construction 2025: industrial strategy for construction—government and industry in partnership", respectively [24,25].

The questions "Will industrial transitions, such as utilizing AI-based new technology, digital transformation, and digitalization, succeed? If so, in order to effectively achieve these transitions, what thoughts will individual players in the construction industry possess?" address the considerations that companies and individuals in organizations will have prior to using AI-based technologies or products. To suggest appropriate answers to these questions, potential users' attitudes towards the acceptance of new technologies or products should be thoroughly examined. When adopting AI-based technologies or products in the construction industry, reviews on the thoughts and attitudes of potential users should be conducted for minimized conflict and stable settlement during the introduction process. Currently, there are many works on the development of AI-based technologies or products to be utilized in the construction industry, whereas works on the acceptance of these are rare [4,5,7,18,22].

Thus, in this research, we aim to understand the factors that impact acceptance of AI-based technologies or products depending on the size of the company in the construction industry, in which various corporates exist. We apply a technology acceptance model (TAM), which is used for research on acceptability and attitudes towards data communication equipment in the management of information systems (MIS) field, to determine the acceptance of and attitudes towards AI-based technologies or products depending on the size of the company. That is to say, by considering influencing relationships between constructs by applying the TAM, we can not only address the acceptance of AI-based technologies or products depending on the size of the company in the construction industry, but we can also provide useful data with respect to developing customized strategies when these technologies are adopted in the future. The second section in this paper presents a theoretical study of AI-based technologies or products in the construction industry, as well as describing the TAM, firm sizes, and innovations. The third section describes the research model, hypothesis setting, and research method. The fourth section analyzes the research model and examines implications of the research. Based on the results of the quantitative verification, the last section suggests the limitations of the research and further study points, as well as providing a summary of the research. The introduction briefly places the study in a broad context and highlights why it is important. This defines the purpose of the work and its significance.

2. Related Work

2.1. Artificial Intelligence (AI) in the Construction Industry

In the construction industry, the utilization of AI-based technologies or products is part of the life cycle of buildings or structures. In general, the life cycle of a building involves the following stages: inception–design–construction–operation and maintenance–demolition [26–28].

Site management and building or facility maintenance are the fields in which AI-based technology development has actively progressed [20,29–31]. There are numerous workers, as well as potential risk factors, on construction sites. Moreover, many construction materials and workers frequently enter the site, so effective and efficient management is crucial. The management of construction materials and inventory through computer-vision-based AI technology is one of the active fields of AI research [32–35]. Shin et al. (2021) developed a computer-vision-based method to count rebar, one of the most important materials in ferro-concrete structures, quickly and precisely [33]. Computer-vision-based machine-learning is used for tracking the number of site workers and the wearing of safety helmets, which is an important site safety management factor, along with material maintenance [36,37]. As summarized in Table 1, computer-vision-based AI technologies are not restricted to the lab, but are recognized for usability, thus positioning them as one of the common technologies on site [32,38–40].

Table 1. AI studies on construction site management.

Authors	Summary	References
Shin et al. (2021)	Rebar size and number counting Convolutional neural network in combination with homography method	[33]
Kamari and Ham (2021)	Volumetric measurements on construction sites Point-cloud methods for 3D segmentation	[41]
Liu et al. (2021)	Review of construction site monitoring techniques based on computer-vision-based technologies	[36]
Yang and Lei (2021)	Adopting YOLOv5 for segmentation of helmet wearing at a construction site	[37]
Xiao et al. (2021)	Construction machine tracking at night on construction sites Illumination enhancement methods providing better object detection under low light conditions	[38]
Yu et al. (2019)	Computer-vision-based 3D motion assessment model for motion capturing of workers	[39]
Fang et al. (2018)	Detecting various objects and workers for on-site safety management Application of improved faster regions with convolutional neural network approach	[40]

Facility maintenance and management of buildings or structures completed through these procedures are important for stable usage and enhancing residents' satisfaction [31,42,43]. In particular, facilities including bridges or tunnels have limits with respect to workers making visual inspections [44–47]. In the case of bridges, it is difficult for workers to visually identify problems due to height. In order to solve these problems, drones and computer vision have been actively adopted [48–50]. In terms of ferro-concrete or steel-frame structures, cracks play an important role in understanding problems with buildings or structures. Computer-vision-based crack detection technology acts as a substitute to overcome a variety of problems, such as workers and equipment falling, human errors, and work limits due to weather [47–49,51]. Furthermore, AI-based technologies or products can function as precautionary maintenance methods that can predict and prevent possible issues. Data collected by various sensors could assist in the preparation of buildings' or structures' maintenance plans, and efficient distribution of resources [29]. Research on the operation and maintenance of buildings is summarized in Table 2.

Table 2. Artificial intelligence research on the operation and maintenance of buildings.

Authors	Summary	References
Jiang et al. (2021)	Proposes a new method to detect and classify concrete cracks for damage management Fewer parameters for portable and speedy application of the suggested method	[51]
Guan et al. (2021)	Pavement distress detection using a vehicle-mounted system to collect pavement surface pictures Modified U-net network architecture to improve computational efficiency	[45]
Dung and Anh (2019)	Concrete crack detection and density evaluation An encoder-decoder FCN for segmentation of images	[46]
Rezaie et al. (2020)	Crack detection in combination with a threshold and deep learning method	[47]
Park et al. (2020)	Real-time concrete crack detection applying YOLOv3-tiny algorithm	[48]
Yang et al. (2020)	Transfer-learning-based deep convolutional neural network for efficient learning	[49]

2.2. Technology Acceptance Model

Finding the reasons behind users accepting or rejecting new information and communication technology (ICT) is one of the important aspects of new technology research [52,53]. The technology acceptance model is one of the models developed to explain and predict users' attitudes against state-of-the-art technology and acceptance of new IT products [54]. First suggested by Davis, Baggozzi, and Warshawet, TAM's theoretical basis is of the theory of reasoned action (TRA), proposed by Fishbein and Ajzen, and the theory of planned behavior (TPB), suggested by Ajzen [55–58].

According to the TRA, the direct decision factor that leads to actual behavior is not the attitude towards action, but the behavioral intention to act [56]. The TRA suggests that real behavior is affected by a behavioral intention to carry out an actual act and the behavioral intention is decided based on attitude and subjective norms [56]. The TPB, which was developed as an extension of rational behavior theory, adding subjective norms and perceived behavioral control variables to its conceptual framework, claims that restricted behavior is under perceptual control through volitional control [57,58]. That is, if individuals perceive that they have little control over their intended actions, they are more likely to refrain from taking action.

The TAM consists of four factors suggested by Davis et al. [54], which are perceived usefulness, perceived ease of use, behavior, and behavioral intention (see Figure 1). Perceived usefulness is defined as the degree of an individual's subjective belief that using a particular system will enhance job performance [54]. This refers to the evaluation of the result that using a product or service with newly introduced technology will improve an individual's job performance or quality of life. Perceived ease of use is defined as the degree of belief that an individual will be able to use a particular type of information technology or system without significant psychological or physical effort [54]. In other words, ease of use is perceived as high when a new product or technology is designed to be user-friendly or when the usage method is similar to an existing work system; it is judged that the system requires less psychological and physical effort to learn. An individual's attitude towards technology usage is revealed as one's belief and emotion towards behavior and affects direct behavioral intention. That is, one's attitude towards technology usage is affected by perceived usefulness and ease of use, and has an effect on the intention [54,55].

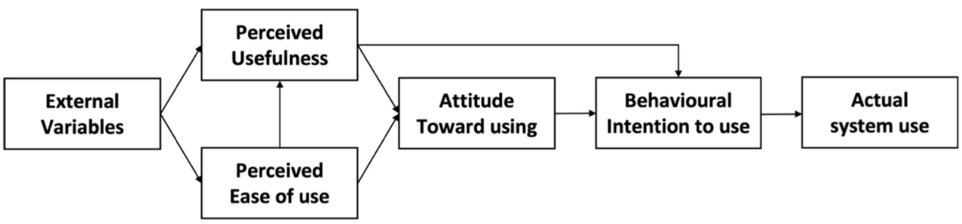

Figure 1. Technology acceptance model [54].

2.3. Firm Size and New Technology Adoption

Many scholars have emphasized the importance of the size of the companies in regard to technology acceptance and adoption [59–61]. Schumpeter (1986) contended that large corporations have enough competence and resources to invest in technology development and innovation, whereas small and medium enterprises do not [62]. Similarly, according to a study by Lee and Xia (2006), corporate size is a surrogate for total available resources and slack within a company, and economies of scale play an important role in accepting innovation [63].

In particular, according to various studies, the size of a company plays a crucial role in developing and accepting new technology, as well as innovation [63–65]. It is said that since new technology development and adoption have attributes such as long-term, grand-scale projects, company size is hugely influential [66–68]. According to a study by Bound et al. (1982), R&D intensity decreases in the beginning and later increases, taking the form of the letter U as company size increases [69]. Based on research results, considering budget processing and research intensity, R&D is more active in large corporates than in small and medium enterprises [70].

However, compared with large corporates, small and medium enterprises possess higher flexibility and adaptability to their surroundings; thus, they are more innovative and find it easier to adopt and utilize new technology [71,72]. Moreover, Mansfield (1981) states that small and medium enterprises have relative advantages over large corporates in technology innovation and development since less effort (time and resources) is required in promoting and mediating cooperation and collaboration between staff. Mansfield also states that when the impact on productivity depending on corporate size and R&D investment is investigated, small and medium enterprises' R&D investment has a larger aggregating effect on the total productivity per factor in the long- and short-term compared with that of large corporates. When these research results are examined, the reality is that studies on corporate size, technology innovation, and R&D are being progressed considerably, whereas research on the acceptance of new technologies or products depending on corporate size is less common.

3. Research Model and Hypothesis

3.1. Overview of the Proposed Model

As suggested in previous research, although there is a consensus on the possibilities and advantages of applying AI-based technologies in the construction industry, methods by which to apply them and maximize profit due to such technologies are not yet clear. Therefore, research on the impact factors to maximize AI-based technologies in the construction industry, and how to apply these in various companies, remains to be carried out. In particular, according to data collected by Statistics Korea, it has been reported that among the registered construction companies in Korea, 98.4% of them are small and medium enterprises and they take 62% of the revenue [73]. Analysis on the impacting factors of AI-based technologies due to the asymmetry between large corporates and small and medium enterprises could play an important role in the application and distribution of AI-based technologies customized for companies. Thus, in this research, we aim to understand the mechanism behind accepting AI-based technologies in the construction industry depending on the company size, based on positively verified research models, such as TAM-related theories.

In order to determine the degree of accepting AI-based technology in the construction industry depending on company size, we achieved verification based on the TAM by Davis (1989) [54]. As shown in Figure 2, the research model suggested in the study uses external variables affecting the intention and usefulness of usage as technological and social factors, as well as individual and organizational capacities, based on previous research. Moreover, along with perceived usefulness, perceived ease of use, and intention to use suggested in the TAM, technology usage satisfaction was chosen as a basic variable. Together with these basic variables, based on the chance that new technology acceptability and individual capacity may vary depending on company size, corporate size was considered as an adjustable variable. In addition, taking into account that individual experience may affect perceived usefulness and perceived ease of use when accepting and using new technology, experience was chosen as an adjustable variable to impact perceived ease of use and perceived usefulness.

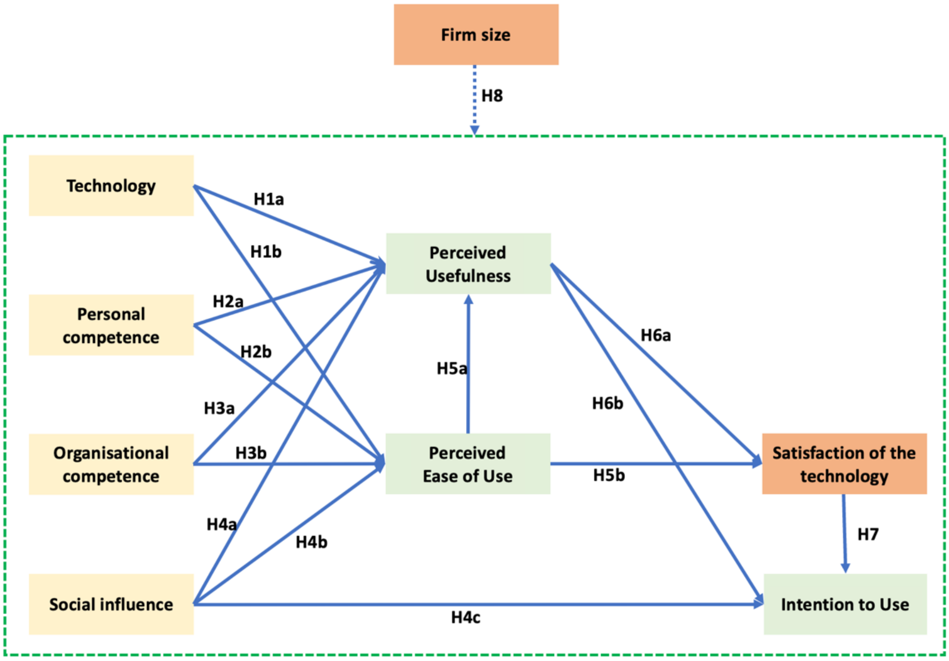

Figure 2. Research model.

3.2. External Variables for AI-based Technology Adoption

3.2.1. Technology

When introducing new technology, it is important to judge whether the technology currently in use or adopted internally is suitable for the organization [74]. For new technology to be stably used and settled, it should not only align with corporate values, but also with the demand for technology and potential user experiences [75]. In other words, even though the new AI-based technology can act as a factor for enhancing work efficiency and competitive advantage, if it shows less compatibility with software or hardware commonly used in the company, the organization or the members may not choose it. In terms of AI-based technology, we suppose that technological attributes show technological suitability, ease of use, and compatibility. Previous research has suggested that for new technology to be used in the construction industry, it should have high compatibility with existing software [76,77]. Compatibility is defined as corresponding with a potential user's previous experience, work practice, system, and requests, and is mandatory in accepting new technology or innovative products. Moreover, it is considered that if new technology is more complicated than the existing technology, users are hesitant to use it even though it is technically superior. Therefore, we set hypotheses as below to verify the effect that technological aspects have on perceived usefulness and ease of use in terms of AI-based technology [74–77].

H1a. *When adopting AI-based technology or products, the technological aspect affects the perceived usefulness of users.*

H1b. *When adopting AI-based technology or products, the technological aspect affects the perceived ease of use of users.*

3.2.2. Personal Competence

The degree of accepting new technology differs depending on an individual's innovativeness or attitude. Research on the TAM has been considering individual traits, such as personal innovativeness as an external variable affecting attitudes, in accepting technology [78–80]. The research suggests there are factors that influence individual traits, such as self-efficacy, an individual's trust of technology, and innovativeness. Bandura (1997) defined self-efficacy as people's beliefs in their capabilities to exercise control over their own functioning and over events that affect their lives [81]. In this study, judgement on self-efficacy affects the cognitive reaction and the affected cognitive reaction has an impact on the expected outcome. Research by Compeau et al. (1999) suggests that new technology users gain confidence with the technology by repeatedly using it for work, and their confidence will affect the expected outcome through the technology. Moreover, individual innovativeness refers to the willingness to accept new technology [82]. Individual innovativeness means early adopters and this can imply how fast one accepts and uses new technology compared with others [78]. Self-efficacy and individual innovativeness represent one's attitude towards encountering new technology, and the positive influence of a person is shown to affect the perceived usefulness and ease of use when accepting new technology. Therefore, on these bases, in this research, we supposed that personal traits affect the acceptance of new technology, and we set hypotheses as below [78–82].

H2a. *When adopting AI-based technology or products, personal competence affects perceived usefulness.*
H2b. *When adopting AI-based technology or products, personal competence affects perceived ease of use.*

3.2.3. Organizational Competence

Individuals within an organization are the main subjects accepting new technology, and one decides whether to accept or not based on influences from organizational structure, culture, and support [83]. The organizational structure mentioned above refers to official procedures concerning decision-making processes, job assignment, and communication, which comprise the series of works and processes with respect to internal announcements when a company adopts a new technology [84–86]. In addition, the organizational members may share reactions or attitudes towards the values or beliefs they share or specific issues; these are designated as organizational culture [87–89]. Members of the organization are unwittingly under the organizational cultural influence, and organizational culture greatly affects attitudes towards adopting new technology. In particular, organizational culture is regarded as one of the important factors for companies to decide on positively accepting new technologies or technological innovations [89]. Hierarchies in communication and active support of the company during technology adoption, which is currently being emphasized, are included in organizational culture. That is, the organizational culture is a comprehensive concept including the goals, support, and policies of an organization in terms of adopting new technology and is regarded as one of the main factors by which companies in the construction industry will decide to use AI-based technology in this research. Furthermore, when it comes to adopting and using new technology, whether or not it will be successfully used is a potential risk, and accepting the risk and the degree of tolerance is useful in forming trust between the members of the organization; these factors will influence active accommodation [80]. Therefore, we set hypotheses as below to verify the impact that organizational competence has on perceived usefulness and ease of use when construction industry companies adopt AI-based technology [83–89].

H3a. *When adopting AI-based technology or products, organizational competence affects perceived usefulness.*
H3b. *When adopting AI-based technology or products, organizational competence affects perceived ease of use.*

3.2.4. Social Influence

Social influence is a factor used to identify differences between one company and another as new methods of communication technologies are developed. Here, social influence refers to the social environment that affects an individual when making a decision, and it also refers to the technological support environment and social atmosphere when adopting new technology [90–93]. In the research on adopting new technologies and the associated attitudes, studies related to the social environment are relatively scant when compared with other factors. However, when core technologies of the fourth industrial revolution such as AI and the metaverse are adopted, discussions on perceiving surroundings and social impacts gradually increase [91,93]. Particularly, for the construction industry, since many stakeholders participate in projects and cooperation among various parties within the supply chain is important, social influence is considered a significant factor in the attitudes towards acceptance of AI-based technology [94,95]. Social influence is an important factor in bridging and bonding, thus its importance is addressed in social capital research [94]. Moreover, it has been reported that in terms of social influence, bridging is an important factor in forming emotional bonds and it greatly affects loyalty to the technology and persistent usage when adopting the technology. Furthermore, bonding is a relational trait that enables forming a strong mutual link in a close relationship; this suggests a closed relationship but refers to one that is able to draw reciprocal emotional support through a network of those with similar backgrounds or characteristics. Therefore, when companies in the construction industry adopt AI-based technology, whether or not to accept the attitudes towards adopting new technology are affected by bridging and bonding within the industry. We set hypotheses as below to verify the impact that social influence has on perceived usefulness and ease of use in adopting AI-based technology [90–95].

H4a. *When adopting AI-based technology or products, social influence affects perceived usefulness.*
H4b. *When adopting AI-based technology or products, social influence affects perceived ease of use.*
H4c. *When adopting AI-based technology or products, social influence affects users' intention to use.*

3.2.5. Perceived Usefulness

In terms of using ICT or systems, usefulness is defined as the user's subjective degree of trust that the technology will enhance the task result [54]. That is, it is a user's belief that one's task performance or quality of life will be improved by using new ICT or systems compared with previous ones. For the TAM suggested by Davis, perceived usefulness is described to affect the attitude and intention of users who adopt new ICT. In addition, when it comes to accepting new ICT or systems, the positive influence that perceived usefulness has on the attitude and intention to use is being verified through many studies in various fields [96–98]. Particularly, the impact of perceived usefulness in the construction industry has been proven in studies on influencing factors and acceptance attitudes in embracing building information modeling (BIM) [80,97]. We set hypotheses as below to verify the impact that perceived usefulness has on adopting AI-based technology in the construction industry.

H5a. *When adopting AI-based technology or products, perceived usefulness affects technological satisfaction.*
H5b. *When adopting AI-based technology or products, perceived usefulness affects users' intention to use.*

3.2.6. Perceived Ease of Use

Davis (1989) defined ease of use as a potential user's degree of belief that using particular information and communication technology or systems will require little physical or psychological effort, or the extent to which one expects to be able to use new technology or systems with little effort [54,55]. Thus, perceived ease of use refers to the degree of personal belief in how easy or difficult it will be for an individual to use a newly adopted technology or product. When practitioners in the construction industry use AI-based technology, the attitude or intention of individuals to adopt or use it may vary depending on the degree of their subjective belief that it is easy to use [54,55,79,91,96]. Therefore, we set the below hypotheses to verify the effect that perceived ease of use has on perceived usefulness and technological satisfaction when adopting AI-based technology.

H6a. *When adopting AI-based technology or products, perceived ease of use affects perceived usefulness.*
H6b. *When adopting AI-based technology or products, perceived ease of use affects technological satisfaction.*

3.2.7. Satisfaction with the Technology

Satisfaction is considered to occur when a user's experience with a product or service exceeds their expectations when compared with prior experiences [99]. Satisfaction is defined as the perceptive, subjective evaluation of a user of an information system based on system quality [100]. Among many subjective evaluation factors for satisfaction, user satisfaction is especially frequently evaluated in information system usage. In particular, user satisfaction tends to show high contentment and outstanding performance when a user willingly uses a system and is not forced to do so by external influences [101,102]. The reason that satisfaction evaluation is important is that it has positive impacts not only on corporate financial performance, but also on non-monetary factors, such as continuous usage, loyalty, and positive references [103,104]. Therefore, we set the below hypothesis by which to verify the effect that technological satisfaction has on usage intention when adopting AI-based technology [100–104].

H7. When *adopting AI-based technology or products, technological satisfaction affects user's intention to use.*

3.2.8. Firm Size

When it comes to adopting new technologies or products for companies, relationships between firm size and new technology adoption are controversial [59–61]. Particularly, large firms play an essential role in the technological innovation, development, and distribution of new products, and act as innovators for technological development [64,65,67].

Since large companies have an absolute advantage in technological innovation in terms of financing, execution, and sustainability, new technology development is more active than it is for small- and medium-sized enterprises (SMEs) [66,68,71]. Firm size is also considered one of the important factors affecting the acceptance and utilization of new technologies. In the case of AI-based technology, which requires a large amount of capital and human resources, firm size is more crucial in adopting new technology. Therefore, we set below a hypothesis by which to verify the effect that company size has on adopting technology in general when adopting AI-based technology [64–68,71].

H8. *When adopting AI-based technology or products, company size affects hypotheses 1–7.*

4. Research Design

4.1. Research Procedure and Data Acquisition

The conducted research involved surveying practitioners in the South Korean construction industry to verify influencing factors when adopting AI-based technology. The construction industry, which is the main area of this study, was defined to include building construction, architectural design, structural design, operation and maintenance, building equipment and machinery, supply chains, and research professionals in this industry.

The research took the form of an online survey in order to verify the set hypotheses. This method was chosen since an online survey is a useful way to meet basic conditions, such as complying with COVID-19 quarantine guidelines, as well as time and space constraints. We consecutively carried out preliminary and main research so as to verify the adequacy of the questionnaires and to develop the research. Preliminary research was conducted from October to November 2022 through semi-structured interviews of experts. Through preliminary research, experts reviewed the adequacy of models and variables suggested in the study, and the main research was conducted based on these developed questionnaires. A total of 500 emails were sent for the main research from December 2022 to January 2023. Among the surveys sent, we received 432 replies, which represented an 86.4% return rate. Normality and outliers of measurement variables were checked through retrieved surveys, and 420 were valid; these were used for analyzing the actual conditions. The results of the technical statistical analysis for the respondents of the collected questionnaires are shown in Table 3.

Table 3. Demographics of respondents (N = 420).

Measure		Frequency	Percentage
Gender	Male	315	75.0
	Female	105	25.0
Age	$20 \leq$ Age < 28	37	16.0
	$28 \leq$ Age < 36	157	37.4
	$36 \leq$ Age < 44	107	25.5
	$44 \leq$ Age < 52	76	18.1
	$52 \leq$ Age < 60	12	2.9
	Age ≥ 60	1	0.2
Type	Construction management	210	50.0
	Design	76	18.1
	Structure design	118	28.1
	Facilities management	8	1.9
	Research and development	8	1.9
Size of company	Large	206	49.0
	Small and medium	214	51.0
Education	Bachelor's degree	246	58.6
	Master's degree	154	36.7
	Doctorate and above	20	4.8
Working experience	$1 \leq$ Years < 5	112	26.7
	$5 \leq$ Years < 10	125	29.8
	$10 \leq$ Years < 15	141	33.6
	Years ≥ 15	42	10.0

The questionnaires used in the research comprised three sections. The first section included a simple explanation of the purpose of the survey, the definition of AI-based technology in the construction industry, and the criteria for classifying company size. In this research, AI-based technology was defined as those commonly used throughout the construction industry, such as computer vision, natural language processing, and machine-learning. In order to provide a demographic analysis of the survey respondents, the second part of the survey was designed to provide information on sex, educational background and level, career, business category, and company size. The last section was composed of 48 questions to determine the factors that influence acceptance of AI-based technology (see Table 3). Each questionnaire used a five-point Likert scale (ranging from "strongly disagree" to "strongly agree") to evaluate the impact factors in adopting AI-based technology.

Valid responses obtained through the email survey were used for various empirical analyses including hypotheses verification. Prior to verification, frequency analysis and technical statistical analysis were performed preferentially on all measurement variables in order to check data input errors, etc. Through this process, error values were removed, and the measurement variables' distribution was checked by identifying the normal distribution, skewness, and kurtosis of variables measured on the consecutive interval scale. Analysis details after implementing these procedures are as follows. First, frequency analysis was conducted to examine the demographic information of respondents. Second, technical statistical analysis was conducted to examine the basic traits (e.g., average, median, mode, standard deviation, skewness, etc.) of continuous variables of the questionnaire (technology, personal competence, organizational competence, social influence, perceived usefulness, perceived ease of use, satisfaction with the technology, and size of company). Third, in order to evaluate the internal consistency of the questionnaire, as well as the convergent validity and conceptual validity of measurement items, reliability analysis (using Cronbach's α coefficient) and confirmatory factor analysis (CFA) were conducted. Lastly, research hypothesis verification through the influencing relationship between responses was undertaken based on structural equation modeling (SEM). We used IBM SPSS 28 and AMOS28 programs to verify the hypotheses for factors affecting the acceptance of AI-based technology.

4.2. Model Validation

4.2.1. Measurement Model

In order to evaluate the overall compatibility of the model, we used the general indexes—the ratio of x^2 to the degree of freedom (df), root-mean-square residual (RMR), goodness-of-fit (GIF), comparative fit index (CFI), and Bentler and Bonnet's normed fit index (NFI)—used for model compatibility measurement [105]. As indicated in Table 4, all x^2/df, RMR, NFI, TLI, and CFI indexes except GFI were shown to exceed the recommended reference values in the research. The GFI was 0.843, which did not meet the recommended standard of over 0.9 in this research. However, it was over 0.8, and according to the results of research by Gefen, Straub, and Boudreau, this can be considered acceptable [106].

Table 4. Results of model compatibility measurement index.

Fitness Indices	Recommended Value	Measurement Value	Structural Model
X^2/df	$\leq$3.0	2.282	2.391
RMR	$\leq$0.1	0.040	0.033
GIF	$\geq$0.9	0.843	0.961
NFI	$\geq$0.9	0.905	0.966
TLI (NNFI)	$\geq$0.9	0.930	0.934
CFI	$\geq$0.9	0.944	0.970

Moreover, seven questions in total were deducted from the research based on verified variables in previous research. Through confirmatory factor analysis of the individual deducted questions, the accuracy and appropriateness of the measurement variables for questions were examined. CFA refers to examining the compatibility of the measurement model to measure the relationships between measurement items and questions [106]. Convergent validity and discriminant validity were analyzed to determine the measurement model's compatibility. In order to check these, factor loading, average variance extracted (AVE), and composite reliability (CR) were measured. In general, if factor loading and AVE are over 0.5, they are considered to have convergent validity, and if the composite reliability value is over 0.7, it is considered to indicate internal consistency and convergent validity of the research model [105]. In this research, CR and AVE were 0.913~0.948 and 0.529~0.779, respectively, which appears to exceed the standard (see Table 5).

In order to examine discriminant validity, covariance between the factors was compared with the average variance extracted from each individual factor [107]. Discriminant validity refers to the process of examining whether there are differences between each question, and whether there is discrimination between them, indicating that they are independent questions rather than the same. We examined discriminant validity using the correlation matrix table derived from the CFA results of the theoretical model. If the AVE value was higher than the square of the coefficient correlation value (i.e., squared correlation), we considered discriminant validity to be acquired [108]. As shown in Table 6, the square root value of the AVE of each latent variable was larger than the coefficient correlation of others. These results show that the research model suggested in the study is discriminant valid.

Table 5. CFA results for measurement model.

Latent Variables	Observed Indicators	β	SE	*t* Value	Cronbach	CR	AVE
Technology	TECH6	0.735	-	-	0.908	0.931	0.692
	TECH5	0.761	0.074	15.205			
	TECH4	0.799	0.075	15.644			
	TECH3	0.870	0.087	15.186			
	TECH2	0.846	0.098	13.983			
	TECH1	0.789	0.099	13.413			
Personal competence	PERS6	0.645	-	-	0.873	0.870	0.529
	PERS5	0.641	0.086	12.592			
	PERS4	0.610	0.096	11.041			
	PERS3	0.762	0.136	11.871			
	PERS2	0.731	0.110	11.722			
	PERS1	0.767	0.123	12.266			
Organizational competence	ORG9	0.923	-	-	0.869	0.944	0.654
	ORG8	0.656	0.042	17.947			
	ORG7	0.941	0.026	36.971			
	ORG6	0.923	0.027	33.583			
	ORG5	0.908	0.030	32.115			
	ORG4	0.917	0.027	33.251			
	ORG3	0.895	0.030	30.098			
	ORG2	0.922	0.027	32.779			
	ORG1	0.900	0.026	30.595			
Socialin fluence	SOC6	0.765	-	-	0.903	0.913	0.638
	SOC5	0.772	0.046	21.720			
	SOC4	0.704	0.058	15.173			
	SOC3	0.741	0.059	15.418			
	SOC2	0.656	0.057	12.329			
	SOC1	0.735	0.053	14.044			
Perceived usefulness	PEOU5	0.859	-	-	0.934	0.948	0.753
	PEOU4	0.882	0.047	22.695			
	PEOU3	0.863	0.043	22.456			
	PEOU2	0.865	0.045	20.930			
	PEOU1	0.844	0.051	19.150			
Perceived ease of use	PU6	0.831	-	-	0.943	0.946	0.779
	PU5	0.888	0.042	24.672			
	PU4	0.851	0.048	21.597			
	PU3	0.860	0.051	20.577			
	PU2	0.817	0.049	20.079			
	PU1	0.818	0.045	20.388			
Satisfaction of the technology	SATF4	0.852	-	-	0.932	0.919	0.739
	SATF3	0.822	0.048	22.108			
	SATF2	0.796	0.049	19.507			
	SATF1	0.819	0.043	20.383			
Intention to use	INT6	0.568	-	-	0.912	0.916	0.652
	INT5	0.587	0.088	10.521			
	INT4	0.873	0.104	11.385			
	INT3	0.847	0.118	10.327			
	INT2	0.795	0.117	10.260			
	INT1	0.810	0.134	10.505			

Note: TECH = technology; PERS = personal competence; ORG = organization competence; SOC = social influence; PEOU = perceived ease of use; PU = perceived usefulness; SATF = satisfaction with the technology; INT = intention to use; β = standardized regression coefficient; SE = standard error; CR = composite reliability; and AVE = average variance extracted.

4.2.2. Hypothesis Verification of the Structural Equation Model

Structural equation model analysis was described in the previous section in order to verify the research hypotheses deducted from the theoretical background. A structural equation is a way of verifying the relations from a cause variable to a result variable based on the theoretical background. In a structural equation, the acceptance of a hypothesis is determined based on the critical ratio (t-value) of CR $\pm$ 1.96 and a significance level of 0.05 or less. Prior to verifying the causal relationship, the overall compatibility of the model was shown to meet the established criteria, including the theoretical model of this study as the appropriate model.

Table 6. Correlation matrix between hypotheses.

	TECH	PERS	ORG	SOC	PEOU	PU	SATF	INT
TECH	1.000							
PERS	0.693	1.000						
ORG	0.731	0.552	1.000					
SOC	0.809	0.676	0.687	1.000				
PEOU	0.555	0.775	0.549	0.653	1.000			
PU	0.724	0.751	0.691	0.737	0.827	1.000		
SATF	0.711	0.692	0.731	0.756	0.760	0.925	1.000	
INT	0.208	0.155	0.307	0.213	0.150	0.182	0.207	1.000

As indicated in Table 7, it can be seen that 11 research hypotheses were verified among the suggested 14 in the theoretical model. The impact of exogenous variables on the acceptance of AI-based technology or products is as shown in Table 7. The exogenous variables with respect to the acceptance of AI-based technology or products appeared to have a positive (+) impact on two aspects, which are the perceived ease of use (β = 0.269, CR = 5.735, $p < 0.001$) and perceived usefulness (β = 0.567, CR = 5.418, $p < 0.001$); thus, the two research hypotheses were chosen. Similarly, the β-values of H3a and H3b, the research hypotheses of organizational competence suggested as exogenous variables, were 0.084 and 0.124, and the CR values were 3.338 and 5.000, which is statistically meaningful ($p < 0.001$); thus, these hypotheses were selected. However, as a result of the structural equation analysis, personal competence was shown to have a positive (+) impact on perceived ease of use (β = 0.564, CR = 12.157, $p < 0.001$), but had a negative (−) impact on perceived usefulness (β = 0.059, CR = 1.380, $p < 0.001$). Analogous to these, social influence was shown to have a positive (+) impact on perceived ease of use (β = 0.290, CR = 5.000, $p < 0.001$), but had a negative (−) impact on perceived usefulness (β = 0.073, CR = 1.551, $p = 1.551$) and on the intention to use technology (β = 0.014, CR = 0.187, $p = 0.851$).

Table 7. Verification results of the structural equation model's influencing relationship on the theoretical model.

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

Note: β = standardized regression coefficient; SE = standardized error; and CR = critical ratio (t-value), *** $p < 0.001$, ** $p < 0.01$.

Moreover, perceived ease of use was shown to have a positive (+) impact on perceived usefulness (β = 0.485, CR = 12.574, $p < 0.001$) in adopting AI-based technology or products, similar to previous research. Along with this result, technology satisfaction newly suggested in the research was shown to be positively (+) affected by perceived ease of use (β = 0.135, CR = 3.563, $p < 0.001$) and perceived usefulness (β = 0.680, CR = 17.563, $p < 0.001$). That is, it can be acknowledged from the research that AI-based technology or products that are technically easy to use and can enhance task performance can provide satisfaction to potential users.

However, personal competence and social influence were shown to have a negative (−) impact on perceived usefulness, thus, hypotheses H2a and H4a were dismissed accordingly. In addition, social influence had no impact on potential users in the construction industry. It was found that the impact of social influence on the acceptance of new technology was similar to previous research, showing a relatively weak effect. In addition, the survey results show that social influence had a negative (−) impact on the intention to use technology (see Figure 3). These results, with respect to adopting AI-based technology or products, are considered to be due to the conservativeness and site-orientation of the construction industry as well as the many manual workers who are site-centered.

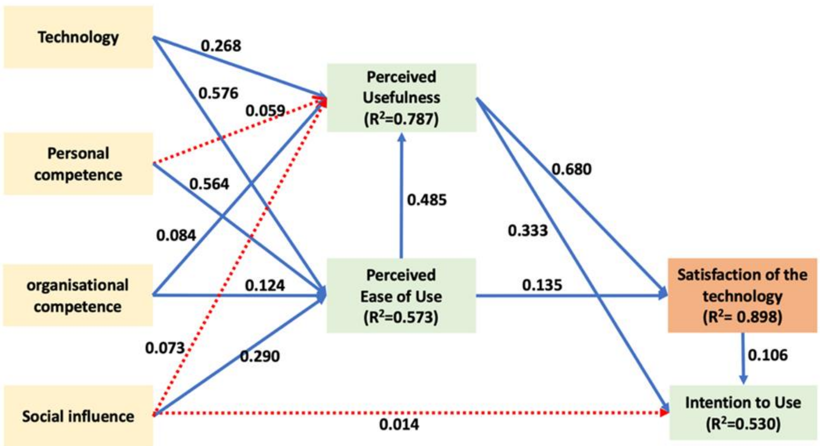

Figure 3. Results of hypothesis testing.

Together with the analysis of adopting AI-based technology or products, an analysis of acceptance in accordance with company size and affecting factors was also conducted with respect to survey respondents. According to the Enforcement Decree of Minor Enterprises Act in Korea, approximately 98% of companies in the construction industry are small and medium enterprises, accounting for 62% of the total industry revenue. Thus, it is considered that analyses on the attitudes and influencing factors of adopting AI-based technology or products depending on company size in the construction industry are necessary in the establishing of strategies to adopt corporate, customized, AI-based technologies or products. We divided the surveyed samples into two groups, large corporations and small- and medium-sized enterprises, to analyze the moderating effects of H1 to H7. Based on this division, the results of the analysis of the adoption of AI-based technologies or products among large corporations and small- and medium-sized enterprises are presented in Figures 4 and 5.

When adopting AI-based technologies or products, the small- and medium-sized enterprise group in the construction industry was identified to have a negative (−) impact on two factors, which were perceived ease of use and perceived usefulness. Unlike the general approach of adopting viral marketing or using influential individuals to promote or disseminate new products or technologies, this study suggests that social influence has little impact on the adoption of AI-based technologies or products among small- and medium-sized enterprises in the construction industry [109–111]. It also showed that organizational competence was a negative (−) factor with respect to perceived ease of use in small- and medium-sized enterprises. As a result of the research, since technological factors, organizational competence, and social influence are factors that could create a negative attitude towards adopting AI-based technologies or products in small- and medium-sized enterprises, it is considered necessary to minimize these factors when adopting.

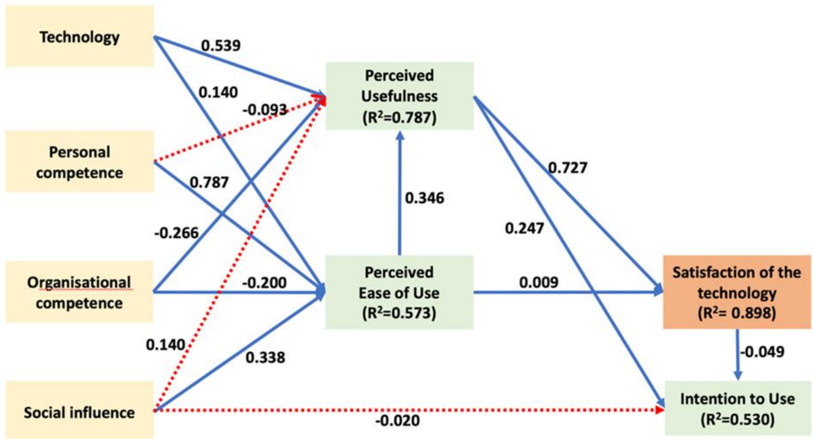

Figure 4. Results of hypothesis testing for large-sized enterprises.

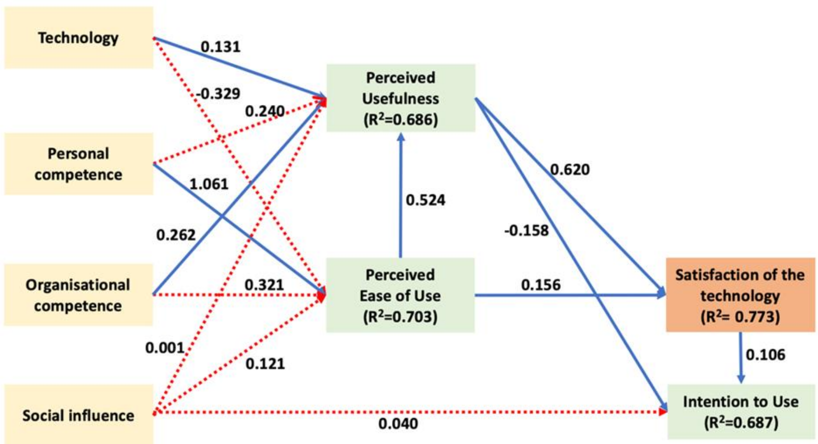

Figure 5. Results of hypothesis testing for small and medium-sized enterprises.

5. Discussion

We empirically researched the relationship between the adoption of AI technology or products and the factors influencing their acceptance in the construction industry based on the size of the company. For empirical research, the study was designed based on previous research and technological satisfaction, and a new hypothesis was added to explain the acceptance of AI-based technologies or products. The below implications were deduced through these empirical verifications.

First, viral marketing, which is an important method for new product promotion, is not commonly used by companies in the construction industry when adopting AI-based technologies or products. Viral marketing is a technique for promotion or providing information about a product that is constantly delivered between the actual users, not through mass media advertisements [109–112]. Due to the emergence of social media and various information-delivering channels, it is utilized as a significant way of distributing new products [112]. However, as a result of our research, recommendations or going viral are not considered effective in adopting AI-based technologies or products in the construction industry. Due to the nature of the products in the construction industry, which involve long-term construction and consideration for human safety after construction, it is believed that the industry avoids the use of good technology or products through viral recommendations [30,35,94,97]. In the construction industry, which uses technology or products verified over long periods, viral promotion of AI-based technologies or products should be avoided.

Next, we determined that organizational competence is an important influencing factor in the adoption of AI-based technologies or products. In companies, there are many occasions where new technologies or products are introduced based on top management's decisions [113–116]. For conservative industries, such as construction, whether to accept or postpone a new technology is decided by the top management. Moreover, the top management of a company plays the role of integrating organizational members, and the greater the uncertainty surrounding AI-based technologies or products, the more important its role becomes in sharing work and promoting participation [117,118]. Furthermore, the knowledge and intuition of top management can foresee and respond to market demand and the company's direction, and their intuition plays a crucial role in producing a core capability to engage with uncertain markets and futures and in setting comprehensive strategies. The positive role of top management in the adoption of new products or technologies, as identified in the results of this study regarding the organization's capabilities, supports previous research findings [119].

Additionally, the research results show that perceived ease of use and perceived usefulness have a positive (+) impact on technological satisfaction. These results are similar to those of Devaraj et al. (2002) and Landrum and Prybutok (2004), from which it could be identified that perceived ease of use and perceived usefulness, as the user's predisposing factors of technological satisfaction, are causes that have a positive influence [120–122]. Furthermore, our results show that the technological satisfaction of a user had a positive (+) impact on the intention to use new technology. This was in accordance with the previous research results of Oliver (1980), who found that user satisfaction has a direct influence on the potential intention of action, such as the continuous intention to use [99]. Thus, along with the previously mentioned top management's decisions, technology being easy to use and useful to users is important to consider when adopting AI-based technologies or products.

6. Conclusions and Implications

6.1. Conclusions

This research has empirically verified the factors affecting the adoption of AI-based technologies or products, depending on the size of company in the construction industry. In order to achieve the research objectives, the TAM was applied to examine influencing factors with respect to the adoption of AI-based technologies or products. Technological and organizational factors were identified to positively influence perceived usefulness and perceived ease of use. Users seemed to think that technology would be useful to their work and would be easy to use when enough capital and education were invested, prior to the company adopting AI-based technologies or products. It was found that perceived ease of use and perceived usefulness indicated satisfaction with new technology, and the higher the intention to use, the higher the satisfaction.

However, as various information-sharing and distribution channels increase, the frequency of using new technologies or products is not achieved through traditional marketing, but through viral marketing via social media; impacts due to influential persons or organizations are also high (REF). As marketing techniques are used as tools for the promotion or dissemination of various products, social influence is regarded as one of the main factors in adopting new technologies or products. However, according to our study, considering adopting AI-based technologies or products is not socially or externally influenced in the construction industry, regardless of company size. This result is believed to be an important implication with respect to the attitudes towards adopting new technologies or products in organizations within the construction industry. That is, organizations within the construction industry selectively choose when to adopt new technologies or products, but not due to external trends or streams.

Furthermore, there were differences in adopting AI-based technology or products depending on the size of the company. The distinct factor between large corporates and small- and medium-sized enterprises was organizational competence. In general, large corporates are able to develop customized technology more easily, as they can handle everything from demand surveys for the technologies they require to their own development. Thus, it was found that the organization's capabilities have a positive (+) impact on the perceived ease of use and perceived usefulness of potential users, as a sufficient reflection of the technology demand from technology users is possible. The results show similarities to previous research, indicating that the size of a company is advantageous in large-scale capital implementation and human resource supply in terms of technological innovation.

6.2. Implications

The results of this research suggest the following: Firstly, in terms of adopting AI-based technologies or products in the construction industry, the relationship between satisfaction with the technology, perceived usefulness, and perceived ease of use was examined. The predisposing factor of intention to use AI-based technologies or products could not be understood by simple perceived traits of technology usage, but was instead based on personal judgments of the technology; satisfaction was an important factor with respect to the intention to use. Additionally, satisfaction with the technology for an individual user was shown to be based on perceived usefulness and perceived ease of use. The research result was similar to that of Oliver (1980) [99], which implies that positive judgment is influential in forming continuous intentions to use the technology. Secondly, we checked whether certain traits have an impact on perceived usefulness, perceived ease of use, technological satisfaction, and the intention to use technology when adopting AI-based technologies or products, and we identified relations between the variables. By applying the TAM as the theoretical outline of the research models for adopting AI-based technologies or products in the construction industry, a theoretical system that could explain a potential technology user's usage attitude or practical usage actions regarding usage intention was prepared. Thirdly, empirical analysis was performed on different influencing factors depending on company size when adopting AI-based technologies or products. In other words, a customized strategy should be set depending on corporate size when introducing new technology. Moreover, constant attention should be paid to technological satisfaction, perceived ease of use, and perceived usefulness for continuous usage of the adopted AI-based technology or product.

6.3. Limitations and Future Research

Despite the suggested implications, the research still has some limitations, which suggest that additional study reflecting these is necessary. First, although the study was conducted to examine differences in company size within the construction industry based on the extracted sample, differences that may arise in the adoption of AI-based technologies or products depending on the industry were not investigated. In other words, it is considered that additional research on the differences in accepting technology and the influencing factors depending on the type of business in the construction industry is necessary. It seems that establishing the basis for setting customized strategies per company size and industry is necessary through additional research in the industry. Moreover, the results show that organizational competence was one of the important factors affecting perceived ease of use and perceived usefulness in this research. Top management's decision-making is an important factor with respect to organizational competence for the adoption of technology, and it seems that research considering factors including top management's attitude and organizational culture is necessary.

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

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