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Acceptance Model of Artificial Intelligence (AI)-Based Technologies in Construction Firms: Applying the Technology Acceptance Model (TAM) in Combination with the Technology–Organisation–Environment (TOE) Framework

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Abstract: In the era of the Fourth Industrial Revolution, artificial intelligence (AI) is a core technology, and AI-based applications are expanding in various fields. This research explored the influencing factors on end-user's intentions and acceptance of AI-based technology in construction companies using the technology acceptance model (TAM) and technology–organisation–environment (TOE) framework. The analysis of end-users' intentions for accepting AI-based technology was verified by applying the structure equation model. According to the research results, the technological factors along with external variables and an individual's personality had a positive influence (+) on the perceived usefulness and the perceived ease of use of end-users of AI-based technology. Conversely, environmental factors such as suggestions from others appeared to be disruptive to users' technology acceptance. In order to effectively utilise AI-based technology, organisational factors such as the support, culture, and participation of the company as a whole were indicated as important factors for AI-based technology implementation.

Keywords: technology acceptance model; technology–organisation–environment framework; artificial intelligence; construction industry; influencing factors

1. Introduction

Historically, human beings have defined innovative eras during which human life and/or society have been drastically altered as revolutions. The agricultural revolution shifted the typical human existence from nomadic to settled; much later but in a surprisingly similar way, the development and utilisation of the steam engine transformed manufacturing and production in what we now call the Industrial Revolution [1]. Since the first Industrial Revolution, other periods of intense change and innovation have been termed the second and third 'waves' or industrial revolutions. Currently, the Fourth Industrial Revolution may be at hand [2–4]. The Fourth Industrial Revolution is moving human existence in another direction. In January 2016, the 46th World Economic Forum was held in Davos, Switzerland, and it was announced that the era of the Fourth Industrial Revolution led by artificial intelligence (AI) was imminent; in addition, 'The Future of Jobs' report suggested that this revolution would disrupt the employment landscape [5]. In the 'Go' game championship held in March 2016 in South Korea, Se Dol Lee, a human competitor, and AlphaGo, an AI competitor, faced off in a five-match showdown during which Se Dol Lee won a single match, and they introduced the world to the potential of AI and machine learning [6]. Over the centuries, our lives and occupational expectations have been upended by technological innovations, and these changes have required us to adapt and accept new technologies and transitions, but many have resisted. For instance, the Luddite Movement of 1811–1817 during the Industrial Revolution destroyed machinery in their blatant rejection and fear of being replaced by the newly invented textile machines [7]. Nonetheless, even those who resist most eventually must accept these radical changes to survive.

AI, the key technology in the Fourth Industrial Revolution, has been used in various fields, changing our lives in various ways [8–10]. Through the utilization of AI in industrial technologies, productivity improvements, accident risk reductions, and improved prediction analyses have been achieved. The construction industry, as a traditional industrial sector, has had few improvements in productivity when compared to others [11–13]. Moreover, the construction industry has been regarded as one of the fields with the slowest informatisation and digitalisation. It has been suggested that this may be due to the nature of the construction industry, where the stakeholders have had a strong resistance to change, as well as to the manual nature of its processes [9,13,14]. Given the achievements attained using AI technologies in various industries, the construction industry should not be content to lag behind [10,15,16]. For example, Germany has conducted 'Construction Site 4.0′, which was similar to Industry 4.0, and the United Kingdom has pursued cost reduction and productivity increases by utilizing digital technologies such as building information modelling through 'Construction 2025 Industrial Strategy: Government and Industry in Partnership' [11,17].

In the era of the Fourth Industrial Revolution, AI has been considered a core innovation, and AI-based technologies have been expanding their applications in various fields. Briefly, AI is a branch of computer science that has focused on developing a form of machine intelligence, akin to the natural intelligence found in animals, namely humans, that is able to learn and employ deductive reasoning similarly to humans [8]. The development of AI technologies in the construction industry in areas such as process and safety improvements, cost efficiency, and production time and labour reduction have been explored by many researchers [9,15,16]. However, since the construction industry has typically been hesitant to accept or adopt new technology, examining the reasons behind their resistance is a crucial step before introducing new innovations that could advance the industry. Only recently has research been conducted regarding users' acceptance and attitudes regarding new information and communication technologies as well as on internet-based services and new electronic devices [18]. Since more nuanced research is sorely needed if the construction industry is to undergo a transformation in line with other industries, our study analysed the relationship between the factors influencing the acceptance of AI-based technology, a pillar of the Fourth Industrial Revolution, and those affecting the construction industry employees. The article is organized as follows: Section 2 briefly reviews related works regarding the technology acceptance models and technology–organisation–environment frameworks to understand the challenges involved in the acceptance and adoption of new technologies. Section 3 explains the research model and the hypotheses of this study to explore the influencing factors of AI-based technologies in construction firms. In Section 4, the results of this study are presented, and the final section discusses the conclusions of this study.

2. Related Works

2.1. Overview of Artificial Intelligence in the Construction Industry

While there have been several definitions of artificial intelligence (AI) in the recent years, it is generally accepted that AI is a field of science and engineering involved in making intelligent machines and programmes that mimic cognitive systems to learn or solve problems [19–21]. AI-based technologies are applied in various fields such as natural language processing, web search engines, understanding human speech, and image recognition. In particular, computer vison-based AI technologies are widely used ones in the construction industry. In the 1950s, there were several attempts to mimic the human visual system to detect edges of objects and classify simple forms of objects into categories such as circles and squares [22–24]. Computer vision technology was commercialised and achieved results as recognising typeface or handwriting using optical character recognition techniques in the 1970s. In recent years, the construction industry has also adopted the computer vision-based technologies for various purposes such as construction site safety monitoring, work efficiency, and structural health checks [9,15,25,26]. Compared to the conventional sensor-based techniques, vision-based techniques would offer potential benefits such as its non-destructiveness, remote measurement, ease-of-use, and ubiquity without installing additional measuring and receiving devices [24,27,28]. In addition, as low-cost, high-performance digital cameras have become common in practice, it is expected that computer vision-based technologies would expand the range of its applications to the construction industry containing many risk factors such as working at height and loading hazardous construction materials at sites [29,30].

Vision-based crack detection methods on the concrete structures, for example, have been one of the most widely applied techniques in the construction industry for the health check and monitoring of the infrastructures and buildings. Koch et al. [27] comprehensively reviewed the current practices of computer vision-based defect detection and condition assessment for concrete and asphalt civil infrastructures. They concluded that while the image-based crack and spalling detection and classification system would be able to automatically detect such defects, the process of collecting the image and video data is not fully automated. Similarly, Jiang et al. [31] proposed a method to detect the concrete damages from images and classify them into four categories: crack, spot, rebar exposure, and spalling. The suggested method performed well under various lighting conditions which would make it difficult to detect concrete surface damages under strong sunlight. In addition, the inference time and accuracy of the proposed method showed an improved performance level compared to the popular CNN algorithms such as YOLOv3 and SSD.

The computer vision-based crack detection methods would be able to detect cracks in different materials regardless of the material images. According to Alipour and Harris [32], the residual convolutional neural network-based deep learning model was suggested to detect and classify the surface cracks on asphalt and concrete with visual differences in colour, contrast texture, and surface features. The proposed method showed the crack detection accuracy of 97.8 and 87.6% for concrete and asphalt, respectively, even though the model has a smaller number of parameters compared to the existing baseline models. In a similar vein, Dung [33] adopted a fully convolutional network for the semantic segmentation of the cracks on a concrete surface. In this study, semantic segmentation was a useful approach in detecting the different cracks in terms of the depth and width of each crack since semantic segmentation is the process of classifying each pixel belonging to the features of the labelled cracks.

Moreover, the image rectification technique would be an effective method not only to monitor the safety of the construction workers but also to count the number of construction materials [34–36]. Son et al. [28] proposed a real-time collision warning system for the prevention of heavy equipment and workers using visual data acquired from cameras. While a number of studies and technologies have proposed to enhance efficiency and health and safety in the construction industry, there is little research that verifies the acceptance of AI-based technologies or explores facilitators and barriers of such technologies in this industry.

2.2. Technology Acceptance Model and Technology–Organisation–Environment Framework

The technology acceptance model suggested by Davis is a powerful tool that explains the influential factors when users adopt new devices or technologies for data communication in the field and has been widely used until recently [37]. It is based on the theory of reasoned action (TRA) and the theory of planned behaviour (TPB) and is acknowledged for being a simple but highly delicate framework for explaining user actions. In Davis's technology acceptance model, embracing new technology relies on two factors, perceived usefulness and perceived ease of use (see Figure 1).

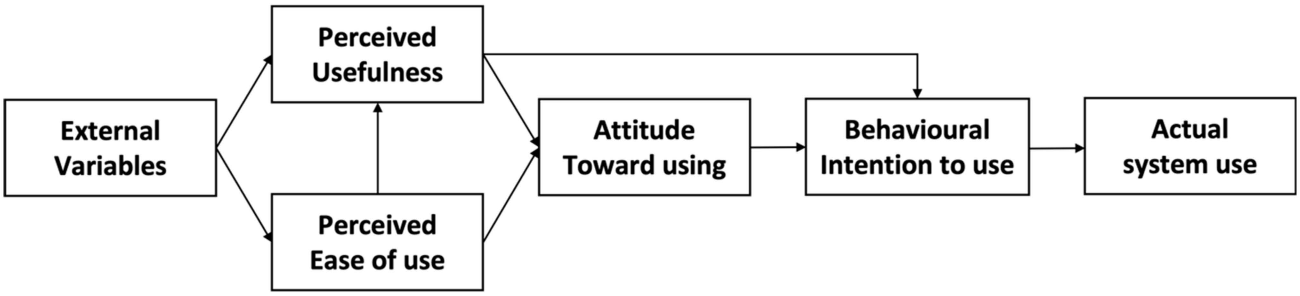

Figure 1. Technology acceptance model [37].

As shown in Figure 1, the technology acceptance model is a theoretical framework in which the user's perceptions of usefulness and ease of use regarding new technology are formed by various external factors, and those factors indirectly impact whether users embrace a new technology as well as their attitudes towards it. Here, perceived usefulness refers to the degree to which the individual believes that using a new technology will enhance their own performance, and perceived ease of use refers the degree to which the individual accepts that the new technology will be easy to adopt without extensive physical effort or a steep learning curve. In the technology acceptance model, there are no restrictions on what external variables may affect the user's perceptions.

External variables of the technology acceptance model used in our research were based on the technology–organisation–environment (TOE) framework suggested by Tornatzky et al. [38] (see Figure 2). The TOE framework provides three contexts that may affect an organisation's information technology adoption process: technological, organisational, and environmental [38,39]. While this framework was suitable for explaining technology acceptance and dissemination from the organisation's point of view, TOE has frequently been applied in research regarding corporations [40–43].

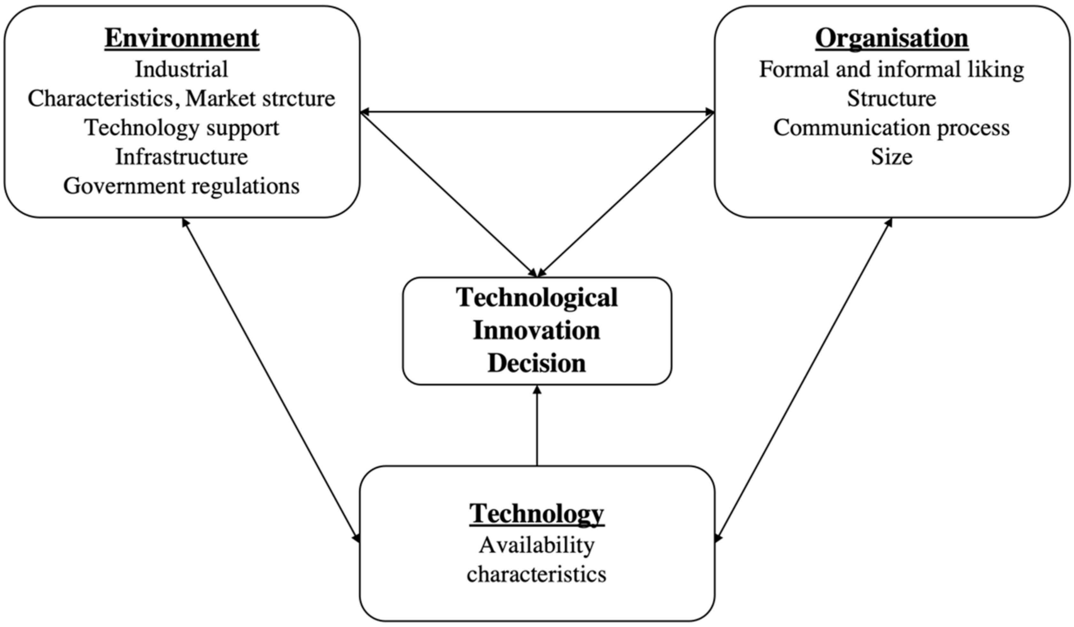

Figure 2. Technology–Organisation–Environment Framework [43].

As indicated in Table 1, the technological context is concerned with the suitability as well as the benefits vs. the difficulties involved when adopting new technology [43,44]. In addition, an organisation should consider its distinctive traits and all possible resources such as its scale, management structure, and organisational culture when considering new technology; these are referred to as 'organisational factors' [38]. In terms of successfully adopting new technology, studies have shown that management leadership and communication played crucial roles as well as organisational scale and resource availability [45]. These organisational factors define the speed and the methods employed when adopting new technology. Environmental factors in the TOE framework refer to the external factors, such as whether the new technology will improve the competitiveness and the efficiency of the organisation's business activities. Governmental regulations and industry trends as well as the existing technology infrastructure across complementary industries can have significant impacts on the degree to which new technology is accepted and the speed at which it can be incorporated.

Table 1. Contextual factors in TOE framework.

Context	Constructed Concepts	Detailed Factors
Technological	All technologies supported inside/outside the organisation [42,46] The ability for technology adoption and suitability of the current technology to the organisation	Relative advantage Conformance Technology complexity
Organisational	Refers to the inherent characteristics and resources the organisation possesses Management leadership and communication play crucial role in innovation Organisation scale and resource availability are also important for decision-making	Corporate size Project range Management support HR scale Competitive advantage Available resources
Environmental	Effectiveness and efficiency factors for organisation's business activities Includes organisation's industry, competitors, governmental regulations, business partners, etc.	Market environment Competition intensity Government policy and regulations Infrastructure of technological resources

3. Research Model and Hypothesis

This research analysed the factors influencing the intention and acceptance of AI-based technology usage by employees and shareholders in construction companies. To achieve this goal, the technology acceptance model (TAM) was used as the model. The external variables affecting usage intention and efficiency were based on previous research concerning individual actions and employing the TOE framework; the research model is depicted in Figure 3. Based on previous research, we concluded that a user's attitude and relevant personal experience regarding new technology was an important factor, so we included it as one of the external variables along with the TOE framework. Therefore, perceived usefulness (PU), perceived ease of use (PEOU), attitude towards usage, and behavioural intention were chosen as basic variables.

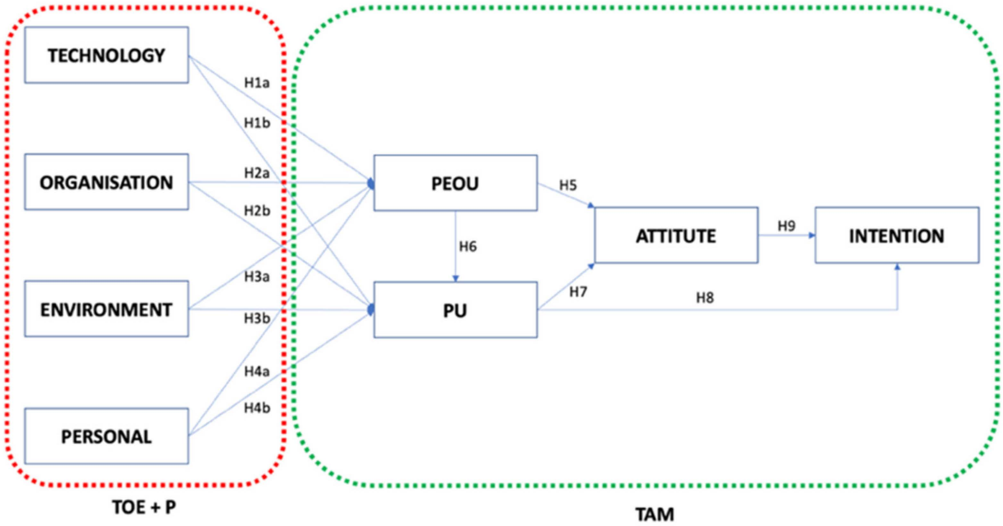

Figure 3. Research model of the research.

3.1. Technological Context

The technological features in AI-based technology refer to the suitability of the technology, the ease of use, its compatibility with the existing technology, and its functional advantages. The selection or adoption of a new technology by an organisation requires the consideration of its advantages or functions, as compared to the existing technology. According to the theory of innovation diffusion by Rogers, it was indicated that the introduction of new or innovative technology by an organisation should coincide with the values of the company, the demand for new technology, and the experience of potential users [47]. Moreover, despite the enormous potential and advantages of new AI-based technologies, if they are incompatible with the current operational systems or will involve significant inconvenience in implementation, organisations may delay their adopting or avoid adopting them altogether. For example, previous research has suggested that low compatibility between current software and hardware and the incoming innovations in a construction organisation were a significant barrier to implementation [48,49]. Furthermore, when new technology has a complicated process or complex interface that is significantly different from the current one, users will resist using it regardless of its benefits [50]. AI-based technology implementation that involves significant changes to long-established routines and steep learning curves can also result in negative impacts on users' PU and PEOU. Therefore, this study set forth the hypotheses below to examine the influence that the technical features have on the end-user's PU and PEOU of AI-based technology.

Hypothesis 1 (H1a). *The technical features of AI-based technologies will have a positive influence on the user's perceived ease of use.*

Hypothesis 1 (H1b). *The technical features of AI-based technologies will have a positive influence on the user's perceived usefulness.*

3.2. Organisational Context

The organisational context refers to the organisational structure and culture, which impact the acquisition, utilisation, and support of new technology [51]. Among the organisational factors, the structure of an organisation influences the development and dissemination of corporate policies and expectations for the implementation of new technology, including the job roles and skills impacted by its adoption. Moreover, the organisational culture influences the employees' attitudes and reactions to a new technology and has been considered an important factor in its acceptance and speed of adoption [51–53].

In this study, organisational support means the recognition of users on policy, culture, resources, and support provided, in terms of accepting AI-based technology. Previous research has shown that organisational members follow a decision when the support is guaranteed or is more than their expectations [54,55]. Furthermore, organisational support not only stimulates members' potential but also plays an important role in enhancing performance on tasks assigned [56–58]. When it comes to organisational context, members tend to actively adopt and utilize new technology not when they are criticised or punished for failures, but rather when these actions are permitted, encouraged, and lead to rewards [59–61]. Therefore, in terms of adopting AI-based technology, this study set forth the hypotheses below to examine the influence that the organisational context has on the end-user's PU and PEOU of AI-based technology.

Hypothesis 2 (H2a). *The organisational support towards AI-based technologies will have a positive influence on the users' perceived ease of use.*

Hypothesis 2 (H2b). *The organisational support towards AI-based technologies will have a positive influence on the users' perceived usefulness.*

3.3. Environmental Context

The environmental context refers to the external social and technological support affecting the adoption of new technology in organisations [38,62,63]. The social influence related to adopting AI-based technology was considered as a variable combining subjective and social norms as well as public image. Concerning the adoption of new technology, there has been very little research concerning the impact of the social environment directly influencing organisational and users' PU and PUOE. However, if we examine the research in other fields, such as healthcare, concerning the influence of the social environment on the adoption of AI technology, it has become an important discussion leading to ongoing research [64,65]. Moreover, since various invested parties take part in construction projects, attitudes regarding the adoption of AI technology may shift due to these outside influences. For example, a competitor's implementation of AI-based technology may encourage others in the field to do the same to remain competitive, or a subcontract's position in the supply chain may give them more influence to shift conservative viewpoints towards new innovation [66,67]. Since adopting new technology more rapidly and agilely than competitors has been considered a way to remain competitive, understanding these environmental impacts is crucial [66,68]. Considering the characteristics of construction projects, this study set forth the hypotheses below to examine the influence that the external business environment has on the end-user's PU and PEOU of AI-based technology.

Hypothesis 3 (H3a). *The environment in which the users work will have a positive influence on users' perceived ease of use.*

Hypothesis 3 (H3b). *The environment in which the users work will have a positive influence on users' perceived usefulness.*

3.4. Personality

Personality refers to an individual's reaction in a particular situation, which is a factor to differentiate oneself from others and expresses patterns of thoughts, emotions, and actions [69]. Personality has been defined in psychology as the aspect of the self that determines the actions or thoughts about oneself and is affected by genetic factors as well as the social, geographical, and cultural environment surrounding a person from birth and into adulthood [70]. Within this context, personality can often explain, in full or in part, the vastly different perceptions and reactions that two people can have to the same stimuli or event [71]. Personality can impact an individual's attitude, intentions, and actions toward the adoption and utilisation of a new technology or device. Therefore, this study set forth the hypotheses below to examine the influence that personality has on the end-user's PU and PEOU of AI-based technology.

Hypothesis 4 (H4a). *Personality and thus the attitude towards new technologies will have a positive influence on the users' perceived ease of use.*

Hypothesis 4 (H4b). *Personality and thus the attitude towards new technologies will have a positive influence on the users' perceived usefulness.*

3.5. Perceived Ease of Use

Previous research on choosing telecommunication technology has shown that the PEOU greatly affected the end-user's PU and attitude towards embracing new technology [72]. As stated earlier, PEOU refers to the degree to which the individual accepts that the new technology will be easy to adopt without extensive physical effort or a steep learning curve. Therefore, this study set forth the hypotheses below to examine the influence that the end-user's PEOU and personality have in the adoption and use of AI-based technology.

Hypothesis 5. *Perceived ease of use will positively influence the perceived usefulness of AI-based technologies.*

Hypothesis 6. *Perceived ease of use will positively influence the attitude toward using AI-based technologies.*

3.6. Perceived Usefulness

It has been proven in previous research that PU positively influences the usage attitudes and intentions in accepting new telecommunication technology or devices [73–75]. Lee and Yu suggested that PU affected the building information modelling (BIM) adoption of construction organisations by analysing the influential factors affecting the implementation of BIM [73]. Therefore, this study set forth the hypotheses below to examine the influence that perceived usefulness has on usage attitude and the intention of AI-based technology users in accepting it.

Hypothesis 7. *Perceived usefulness of AI-based technologies will positively influence the attitude towards using them.*

Hypothesis 8. *Perceived usefulness of AI-based technologies will positively influence the intention of using them.*

3.7. Attitude towards Utilisation

The attitude towards utilisation is a subjective decision of a user regarding the new technology or device to be used, which may be positive or negative. According to attitude models and decision theory, using new technology has been shown to be dependent on a user's attitude and its influence on decision making [76,77]. For instance, in the research by Yuan et al., the user's attitude towards BIM implementation was a positive factor for adopting BIM in a sustainable management project [58]. Therefore, we considered a user's decision to use new AI-based technology as dependent on the user's attitude. Therefore, this study set forth the hypotheses below to examine the influence that a user's attitude has on their intention to use AI-based technology.

Hypothesis 9. *The attitude towards using AI-based technologies will positively influence the behavioural intention.*

4. Research Design

4.1. Procedure on Research and Data Collection

In order to verify the aforementioned hypotheses, we conducted a survey on participants who worked for construction companies. The questionnaire had three sections. The first section of the survey briefly explained the characteristics of AI-based technology and its usage along with relevant pictures. The second section queried the participant's gender, age, educational background, employment, and work experience for demographic analysis (see Table 2).

Table 2. Demographics of the respondents (N = 241).

Variables	Category	Frequency	Percentage (%)
Gender	Male	167	69.3
	Female	74	30.7
Age group	20–25	16	6.5
	26–35	71	22.8
	36–45	105	43.6
	46–55	57	23.7
	Above 56	8	3.3
Work experience	0–5 years	48	19.9
	6–10 years	82	34.0
	11–15 years	74	30.7
	Above 16 years	37	15.4
Education	Bachelor's degree	157	65.1
	Master's degree	67	27.8
	Above	17	7.1

To understand the users' intention towards embracing AI-based technology, the last section provided 25 detailed questions (see Table 3). In order to obtain valid evaluation criteria regarding users' attitudes towards using AI-based technology in a construction organisation, four AI experts with an average of seven years of experience in the construction field pre-reviewed the questionnaire before distribution to review it for validity and accuracy. Responses were provided using a five-point Likert scale.

Online survey e-mailing links were used to acquire data, and a total of 267 responses were collected. Among the responses, those with all same answers or that did not reply were excluded, and 241 valid samples were used for the research. The hypotheses on AI-based technology acceptance attitudes suggested in the research were checked for validity by utilising IBM SPSS Statistics 26 and AMOS 26 programmes.

Table 3. Hypotheses of the research.

Variables	Hypotheses		Definition
Technology	H1	a	The technical features of AI-based technologies will have a positive influence on the users' perceived ease of use.
		b	The technical features of AI-based technologies will have a positive influence on the users' perceived usefulness.
Organisation	H2	a	The organisational support towards AI-based technologies will have a positive influence on the users' perceived ease of use.
		b	The organisational support towards AI-based technologies will have a positive influence on the users' perceived usefulness.
Environment	H3	a	The environment in which the users work will have a positive influence on users' perceived ease of use.
		b	The environment in which the users work will have a positive influence on users' perceived usefulness.

Table 3. *Cont.*

Variables	Hypotheses		Definition
Personality	H4	a	Personality and thus the attitude towards new technologies will have a positive influence on the users' perceived ease of use.
		b	Personality and thus the attitude towards new technologies will have a positive influence on the users' perceived usefulness.
Perceived ease of use	H5		Perceived ease of use will positively influence the perceived usefulness of AI-based technologies.
	H6		Perceived ease of use will positively influence the attitude towards using AI-based technologies.
Perceived usefulness	H7		Perceived usefulness of AI-based technologies will positively influence the attitude towards using AI-based technologies.
	H8		Perceived usefulness of AI-based technologies will positively influence the intention of using AI-based technologies.
Attitude	H9		The attitude towards using AI-based technologies will positively influence the behavioural intention of using AI-based technologies.

4.2. Verification of Research Model

This study tested the suitability of the research model for the data it was intending to acquire before verifying its reliability and validity. Using substantiating indices typically employed for suitability verification, all values were above the recommended levels, as shown in Table 4. Therefore, the research model would be suitable for verifying our hypotheses.

Table 4. Evaluation of fit indices of the studied model.

Fitness Indices	Recommended Value	Measurement Value
X^2/df	$\leq$3.0	1.855
RMR	$\leq$0.1	0.022
GFI	$\geq$0.9	0.902
NFI	$\geq$0.9	0.892
TLI (NNFI)	$\geq$0.9	0.914
CFI	$\geq$0.9	0.945

Furthermore, in order to check whether latent and measurement variables were properly associated in the research model, confirmatory factor analysis (CFA) was conducted. The analysis of reliability among measurement variables was substantiated with Cronbach's alpha coefficient by applying internal consistency. In internal consistency, a model is considered reliable when Cronbach's alpha coefficient value is over 0.7, and all the values of the measurement variables in the study exceeded the reference value, as shown in Table 5; therefore, the model was reliable.

Next, in order to verify the convergent and discriminant validity of the measurement model, factor-loading, average variance extracted (AVE), and composite reliability (CR) were calculated. In general, convergent validity is confirmed when factor-loading and AVE values are over 0.5 and CR values are over 0.7 [78]. As for discriminant validity, each latent variable's factor-loading has to be bigger than the cross-loading in general, and AVE's square root value has to be bigger than the other's correlation coefficient. As shown in Tables 5 and 6, all measurement factors of the suggested research model suggested are reliable with convergent and discriminant validity.

Table 5. Convergent validity of the measurement model.

Variables	Items	Standardised Factor Loadings	Cronbach's α	Average Variance Extracted (AVE)	Composite Reliability (CR)
Technology	TECH1 TECH2 TECH3	0.878 0.826 0.725	0.927	0.859	0.948
Organisation	ORG1 ORG2 ORG3	0.432 0.525 0.771	0.842	0.709	0.873
Environment	ENV1 ENV2 ENV3	0.704 0.743 0.706	0.865	0.748	0.899
Personality	PER1 PER2 PER3	0.732 0.698 0.762	0.888	0.789	0.918
Perceived Ease of Use	PEOU1 PEOU2 PEOU3	0.691 0.765 0.728	0.825	0.681	0.863
Perceived usefulness	PU1 PU2 PU3 PU4	0.697 0.816 0.646 0.729	0.881	0.776	0.932
Attitude	ATT1 ATT2 ATT3	0.635 0.806 0.544	0.865	0.749	0.897
Intention	INT1 INT2 INT3	0.596 0.656 0.744	0.836	0.698	0.873

Table 6. Correlation matrix of the measurement model.

	TECH	ORG	ENV	PER	PEOU	PU	ATT	INT
TECH	0.927							
ORG	0.705	0.842						
ENV	0.611	0.700	0.865					
PER	0.671	0.458	0.462	0.888				
PEOU	0.843	0.769	0.632	0.614	0.825			
PU	0.606	0.719	0.602	0.288	0.604	0.881		
ATT	0.638	0.503	0.463	0.606	0.732	0.412	0.865	
INT	0.402	0.199	0.390	0.3245	0.496	0.384	0.517	0.836

4.3. Verification and Analysis of the Hypotheses (Structural Equation Modelling Analysis)

Confirmatory factor analysis and path analysis were conducted by utilising IBM AMOS 26 so as to verify the hypotheses of this study. Whether to accept the hypothesis was based on a CR (t-value) over ±1.96 and under 0.05 significance level. The results of structural model path analysis based on the output calculated are shown in Table 7.

As indicated in Table 7, 9 out of the 13 research hypotheses were confirmed. Among the external variables of technology, organisation, environment, and personality, personality positively (+) influenced the end-user's PEOU and the PU of AI-based technology (see Table 7). Therefore, hypotheses H4a and H4b were confirmed. Similarly, it was found that technology and organisational factors have a positive influence (+) on the end-user's PEOU of AI-based technology. The positive influence of technology factors on the end-user's PEOU agreed with the results of previous research (β = 0.567, t = 5.408, $p < 0.001$); therefore, hypothesis H1a was confirmed. As a result of the structural equation analysis, technology and organisational factors appeared to have a negative influence (-) on the end-user's PEOU of AI-based technology.

Table 7. Results of the structure equation model.

Hypotheses	Relationship			β	SE	CR	ρ	Results
H1a	PEOU	←	TECH	0.567	0.088	5.408	***	Supported
H1b	PU	←	TECH	0.429	0.143	2.426	0.015	Not supported
H2a	PEOU	←	ORG	0.296	0.189	2.625	**	Supported
H2b	PU	←	ORG	−0.092	0.212	−0.419	0.675	Not supported
H3a	PEOU	←	ENV	0.021	0.092	0.206	0.837	Not supported
H3b	PU	←	ENV	0.196	0.106	1.633	0.103	Not supported
H4a	PEOU	←	PER	0.144	0.078	1.809	**	Supported
H4b	PU	←	PER	−0.344	0.095	−3.419	***	Supported
H5	PU	←	PEOU	0.490	0.266	2.974	***	Supported
H6	ATT	←	PEOU	0.945	0.124	7.582	***	Supported
H7	ATT	←	PU	−0.279	0.096	−3.008	**	Supported
H8	INT	←	PU	0.333	0.072	4.030	***	Supported
H9	INT	←	ATT	0.472	0.079	4.976	***	Supported

SE is Standardised Error, CR is Critical Ratio (*t*-value). *** $p < 0.001$, ** $p < 0.01$.

Environmental factors had a negative influence (-) on the end-user's PEOU and PU of AI-based technology; therefore, hypotheses H3a and H3b were both rejected. Moreover, the influencing relationship between attitude, PEOU, and PU towards AI-based technology was similar to previous research results. The end-user's PU of AI-based technology had a positive influence on their PEOU and their attitude. In this study, one of the factors with the most important influence on embracing AI-based technology in construction organisations was the end-user's PU (β = 0.945, t = 7.582, $p < 0.001$). In contrast, the environmental factors had little impact in adopting new technology (β = 0.021, t = 0.206).

4.4. Discussion

Nine out of the thirteen hypotheses in this study were confirmed. The positive influence of technical features in adopting new technology has been proven by many researchers [79–81]. This is especially true because most new technology such as that found in telecommunication is chosen based on its abilities to enhance the end-user's work performance. In other words, in order to effectively adopt new AI-based technology, selecting a technology with sufficient user benefits and performance enhancement should be prioritised for end-user PU and PEOU.

The research results showed that organisational factors considering external variables also had a positive impact on end-user PEOU, which was similar to the result for the technological factors. However, the organisational factors had a negative impact (-) on the end-user's PU of AI-based technology. According to research by Orlikowski [82], contextual settings such as organisational cultures and structures affected users' acceptance of new technology, and other research confirmed that organisational influence had a positive effect on the adoption of new technology [83–85]. Although this research stated that users reported that AI-based technology was easy to utilise based on their past experiences, it was thought to have a negative impact (-) on PU over time.

The environmental factors appeared to have no influence on the end-user's PU and PEOU in construction organisation's AI-based technology implementation. These results may be related to an organisational tendency towards conservatism [12,86,87]. Despite receiving high social interest or being discussed many times in media such as in newspapers or broadcasting, new technology may still need to be tested and trialled before receiving broader acceptance in these types of conservative organisations [88–91]. In construction projects, one of the top priorities is safety, and AI-based innovations will be verified over time in their abilities to support that priority. However, as compared to the steel industry that often has similar conservative leanings in terms of the adoption of new technology, the construction industry has moved farther ahead in enhancing productivity using AI-based technology. Furthermore, considering that many countries have been pursuing various innovative construction policies for advancement, the use of AI-based technology in the construction industry may develop more rapidly in the future. [11,17].

In addition, among the influential factors in the end-user's acceptance of AI-based technology, PU and PEOU appeared to have a positive influence (+) in the research, and this was similar to the results of previous research exploring the influential factors in embracing BIM [48,49,58]. This result also aligns with results in other fields that analysed influential factors on new technology utilizing TAM. When AI-based technology is introduced in a construction organisation, the technology must, therefore, be user-friendly and should promote work efficiency and increased productivity.

AI-based technology has advantages such as decreasing human error, improving productivity due to repetitive-task fatigue in humans, and predicting risks and taking pre-emptive actions via big data analysis [9,15,34,92]. When a construction organisation is adopting an AI-based technology with these advantages, this study presents considerations that should be involved in the implementation strategy. The adoption of AI-based technology in construction organisations requires user-friendly interfaces with user-valued features that will enhance productivity and work performance as well as an optimized, sensitive implementation rollout with consideration for the company culture and employee morale. In countries such as South Korea where the government is actively developing and utilising AI-based technologies and encouraging their implementation in industrial applications, environmental factors play a significant role in encouraging end-user PU and PEOU, which could be beneficial in conservative organisations such as those in the construction industry. Furthermore, it is expected that facilitating factors suggested in this study would be beneficial to any construction companies to adopt AI-based technologies. AI-based technologies would make it possible for the construction firms to achieve the competitive advantages as well as the improvement of the productivity. Accordingly, it is expected that the successful implementation of such technologies would be possible to consider the facilitating factors proposed in this study.

5. Conclusions

This research analysed influential factors on end-user's PU and PEOU of AI-based technology in construction companies, which impact the speed and efficiency of their implementation. Using the technology acceptance model and the TOE framework, the analysis of end-user intention was verified by applying the structure equation model. According to research results, the technological traits assumed with the external variable and personality appeared to have a positive influence (+) on PU and PEOU. Conversely, external environmental factors such as suggestions from others appeared to be a disruptive factor in an end-user's technology acceptance. To effectively implement and utilise AI-based technology, organisational factors such as the support and the participation of the company as a whole appeared to be important factors.

AI is a core technology of the Fourth Industrial Revolution and is expanding its application in diverse fields. Various technologies with AI are being developed in the construction industry and have proven benefits. Nonetheless, although we compete for the introduction of AI technologies as if they are a global panacea, little discussion has been had regarding which factors facilitate its acceptance and implementation by the workers who must adapt to it. The research analysis of factors influencing end-users' PU and PEOU of AI-based technology in construction organisations are provided as practical guidelines for construction organisations that are considering adopting AI-based technology.

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