Korean Journal of Construction Engineering and Management
Vol. 26, No. 3, pp. 087-096 / May 31, 2025
https://dx.doi.org/10.6106/KJCEM.2025.26.3.087
pISSN 2005-6095
eISSN 2465-9703
www.kjcem.org

Barriers to the Adoption of Computer Vision-based Object Recognition in Construction Sites

- Analyzing Barriers to Safety Technology Adoption Using the Technology Acceptance Model -

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Abstract : This study investigates the factors hindering the adoption of computer vision object recognition technology in construction sites, focusing on user perception and technology acceptance. Using the Technology Acceptance Model (TAM) alongside factors such as price efficiency, social influence, and associated experience, the research reveals key reason. Price efficiency significantly enhances both perceived ease of use (PEOU) and PU, suggesting economic benefits make the technology more accessible and beneficial. Conversely, social influence negatively impacts PEOU, indicating that higher social pressure may make the technology seem more challenging to use. Associated experience positively affects PU, implying that prior experience makes the technology more valuable to users. Both PEOU and PU positively influence the intention to use the technology, with PEOU having a particularly strong effect. Emphasizing economic efficiency and ease of use is crucial for technology adoption, while addressing social influence through education and awareness can mitigate its negative impact. Survey results highlight the importance of cost support, showing users are sensitive to financial aspects. These findings offer valuable insights for promoting advanced safety technologies in the construction industry.

Keywords : Computer Vision, Object Recognition, Technology Acceptance Model, Construction Safety

1. Introduction

1.1 Research Background and Objectives

The construction industry accounts for 53% of all industrial accident fatalities in South Korea, making up more than half of the total across all industries. To address this issue, the government has introduced policies mandating the use of Smart Construction Safety Technologies, such as location-tracking safety helmets and smart full-body safety harnesses, aiming to create a safer work environment and strengthen on-site safety management. (Ministry of Employment and Labor, 2022).

Among these smart safety devices, computer vision technology applicable to construction sites has recently gained attention. (Seo et al., 2015). Computer vision technology enables computers to precisely recognize images and videos, similar to human vision. It involves processes such as image data collection, object recognition, feature extraction, offline learning, and object classification through monitoring. (Jin et al., 2023). Through this process, computers continuously detect both moving and stationary 3D objects related to assigned

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Received December 11, 2024; **revised** February 3, 2025
accepted April 8, 2025

tasks. Upon detecting a hazard, they send a signal to safety managers, enabling real-time monitoring. (Li et al., 2024). Various object recognition algorithms have been developed, including YOLO (You Only Look Once) for real-time object detection, Faster R-CNN (Region-based Convolutional Neural Network) for high-precision detection, and Mask R-CNN, which simultaneously performs object detection and segmentation (Kulinan et al., 2024).

These technologies help prevent accidents caused by worker negligence and human error while significantly improving safety management efficiency. As safety becomes increasingly crucial in construction sites, computer vision technology is gaining recognition for its immense potential. Although this technology shows great potential for real-time worker behavior detection and hazard identification, its widespread adoption in construction sites remains limited due to high implementation costs, low user awareness, and regulatory barriers (Guo et al., 2021). A 2019 survey on the adoption of big data and artificial intelligence in the construction industry found that 72.6% of respondents were aware of these technologies, and 63.2% believed they would become widely adopted within the next decade. However, only 28% planned to implement them within that timeframe, reflecting a relatively low commitment to adoption.

This indicates that significant barriers to adopting computer vision technology still remain. This study quantitatively analyzes the barriers to adopting computer vision-based object recognition technology, focusing on preventing safety accidents in construction sites, based on the Technology Acceptance Model (TAM). Through survey data, this study provides empirical evidence on technology adoption costs and priority application areas. While these topics may already be well known, empirical analysis through surveys has been limited. In this context, this study holds significance by offering both policy and academic implications.

1.2 Research Methods and Procedures

This study focused on investigating user perceptions of computer vision technology as part of smart safety equipment, particularly its effectiveness in preventing worker errors, injuries, and fatal accidents. The survey targeted equipment users, workers benefiting from the technology, construction industry professionals, and individuals with relevant expertise. The study first reviewed previous research to examine the importance of user perception in the technology adoption process based on theoretical models and assessed the implementation status of smart safety policies. It also explored the overall characteristics and potential applications of computer vision technology. Subsequently, a research model on computer vision technology was developed based on theoretical frameworks. Path coefficients derived from this model were analyzed to identify key barriers in the technology adoption process. Through this analysis, the study aims to systematically evaluate the factors influencing technology adoption, identify barriers hindering the adoption of computer vision technology, and propose strategies for improvement.

2. Theoretical Review

2.1 Existing Research

Among existing studies, one research utilized the TAM to examine the BIM adoption perception of construction managers (CMr) in South Korea. Through a survey, the study analyzed the factors influencing BIM adoption. (Chung & Chin, 2015). Additionally, a study on smart devices analyzed the perception differences among users of smart safety harnesses in South Korean construction sites through semi-structured in-depth interviews (2021). While these studies have contributed to understanding user perceptions of smart technologies applicable to construction sites, there seems to be relatively limited research applying the TAM framework to computer vision technology. Existing studies on computer vision have primarily focused on the theoretical performance and applicability of the technology, with limited research addressing the specific factors that hinder its adoption. Accordingly, this study aimed to quantitatively analyze the barriers hindering the adoption of computer vision-based object recognition technology through a survey based on the TAM model.

2.2 Overview and Characteristics of the Technology Acceptance Model (TAM)

The foundation of theoretical models on technology adoption was established with the introduction of the TAM by Davis. Davis, in proposing the Technology Acceptance Model (TAM), asserted that technology adoption and user behavioral intention are fundamentally determined by two core constructs: Perceived Ease of Use (PEOU) and PU.(Viswanath and Davis, 2000). Subsequently, the robustness and credibility of the TAM model were further reinforced through the integration of additional variables related to technology usage.(Viswanath & Bala, 2008). In the field of architectural engineering, the TAM model has been widely utilized, particularly in ongoing studies analyzing the impact of user perceptions on the adoption of new technologies. Furthermore, numerous studies have confirmed that, in addition to PU and PEOU, factors such as Price Efficiency (PE), Social Influence (SI), and Associated Experience (AE) also influence the TAM model. These findings demonstrate the high flexibility and applicability of the TAM model in explaining technology adoption.

3. Research Methodology

3.1 Research Design

This study established key variables related to user perception and technology adoption by reflecting the characteristics of computer vision-based object recognition technology. Based on these variables, a survey was conducted to examine user perceptions. In this process, the definitions and interrelationships of each variable were clearly specified to ensure the structural rigor of the study The research model adopted in this study was built upon the TAM while incorporating additional variables in an extended framework.

3.2 Definition of Variables

The key variables include PEOU, PU, SI, PE, AE, and Intention of Use (IU). PU and PEOU constitute the core components of the TAM model, while the remaining variables have been extensively validated through prior research.

3.2.1 Price efficiency

Price Efficiency refers to the extent to which users perceive a technology or system as cost-effective. When users recognize a technology as economically efficient, its likelihood of adoption increases.

- H1-1: Price Efficiency is expected to have a significant impact on PEOU
- H1-2: Price Efficiency is expected to have a significant impact on PU.

3.2.2 Social influence

Social Influence reflects how a particular technology or system is perceived within a social context. Social pressure and expectations play a crucial role in shaping users' technology adoption decisions.

- H2-1: Social Influence is expected to have a significant impact on PEOU.
- H2-2: Social Influence is expected to have a significant impact on PU.

3.2.3 Associated Experience

Associated Experience refers to a user's prior exposure to similar technologies or systems. Previous experience plays a critical role in determining how easily users can learn and adapt to new technologies.

- H3-1: Associated Experience is expected to have a significant impact on PEOU.
- H3-2: Associated Experience is expected to have a significant impact on PU.

3.2.4 Perceived Ease of Use

PEOU refers to the degree to which users believe that a particular technology or system is easy to use. It plays a crucial role in lowering initial barriers to technology adoption. When a technology is perceived as highly user-friendly, users are more likely to adopt and utilize it effectively.

- H4-1: PEOU is expected to have a significant impact on PU.
- H4-2: PEOU is expected to have a significant impact on IU.

3.2.5 Perceived Usefulness

PU refers to the extent to which users believe that a particular technology or system will enhance their job performance. It is regarded as one of the most critical variables in the TAM model. Perceived Usefulness significantly influences users' likelihood of adopting and

Table 1. Survey Questions by Variables

Variable		Description
Price Efficiency	PE 1	I think the cost of adopting computer vision technology is reasonable.
	PE 2	I feel that computer vision offers high cost-effectiveness.
Social Influence	SI 1	Social systems encourage the use of computer vision technology on construction sites.
	SI 2	Supervisors and colleagues recommend using computer vision technology.
Associated Experience	AE 1	I have some experience using computer vision technology.
	AE 2	I am familiar with computer vision technology because I have used it before.
Perceived Ease of Use	PEOU 1	I find it easy to use computer vision for my work on construction sites.
	PEOU 2	Becoming proficient in using computer vision technology is straightforward.
Perceived Usefulness	PU 1	Using computer vision technology can enhance my work performance.
	PU 2	Applying computer vision technology to my tasks is effective.
Intention of Use	IU 1	I will frequently use computer vision technology on construction sites.
	IU 2	I will recommend others • to use computer vision technology.

utilizing the technology.

- H5: PU is expected to have a significant impact on IU.

3.2.6 Intention of Use

IU represents a user's willingness to adopt a particular technology or system. It serves as a critical predictor in the pre-adoption stage, influencing the actual usage behavior. According to the TAM model, variables such as PU and PEOU have been shown to influence IU. These variables are instrumental in predicting how frequently and consistently users are likely to adopt and continue using a given technology.

3.3 Data Collection Methods

As shown in 〈Table 1〉, the survey used in this study comprised 18 items, including two each for PE, SI, AE, PEOU, and PU. All variables were measured using a five-point Likert scale. The survey was conducted over ten days, from May 23 to May 29, 2024. Participants were required to have prior knowledge of computer vision-based object recognition technology. To ensure this, preliminary screening questions were included, such as: 'Have you heard of object recognition technology?', 'Have you used a system that utilizes computer vision technology?', and 'Are you familiar with computer vision-based safety management in construction sites?' A total of 64 responses were collected and used as research data.

4. Data Analysis and Results

4.1 Sample Characteristics

The analysis of the sample is presented in 〈Table 2〉. The gender distribution comprised 61 males (95.3%) and 3 females (4.7%). The age distribution was as follows: 23 participants in their 20s (35.9%), 23 in their 30s (35.9%), 11 in their 40s (17.2%), 6 in their 50s (9.4%), and 1 participant aged 60 or older (1.6%). Additionally, 47 participants (73.4%) were employed in construction-related occupations, while 17 (26.6%) were in non-related fields.

Table 2. Characteristics of the sample

Category	Group	Count	Ratio
Gender	Man	61	95.3%
	Woman	3	4.7%
Years	20	23	35.9%
	30	23	35.9%
	40	11	17.2%
	50	6	9.4%
	Over 60	1	1.6%
Related	Related	47	73.4%
	Unrelated	17	26.6%

4.2 Reliability and Validity Assessment

This study performed Partial Least Squares (PLS) analysis using the plspm library in the R statistical programming language. The bootstrapping method was applied with 2,000 resampling iterations based on existing literature, ensuring reliable results even with a small sample size and enhancing the stability of the analysis (Bujang et al., 2018; Kline, 2023). The survey and variables were designed to assess users' subjective perceptions, and the reliability and validity of the study were evaluated accordingly. To examine the reliability of the variables, Cronbach's Alpha and Composite Reliability (CR) were computed. Cronbach's Alpha measures the internal consistency of a measurement instrument, where a value of 0.6 or higher is generally considered 'acceptable,' 0.7 or higher 'good,' and 0.8 or higher 'excellent' (George & Mallery, 2003; Cho & Kim, 2014). In this study, the overall Cronbach's Alpha value was computed as 0.812, indicating that the measurement instrument exhibits at least 'good' reliability. Most variables met the reliability threshold; however, the Cronbach's Alpha value for the Social Influence variable was 0.611, suggesting relatively low internal consistency but still within the 'acceptable' range. In contrast, CR is another metric used to evaluate the consistency of a measurement instrument. All variables recorded values above 0.7, demonstrating high reliability. These results confirm that most variables exhibit strong reliability, although some variables may require further refinement to enhance internal consistency.

4.2.1 Indicator Reliability

In structural equation modeling (SEM), one of the key factors for assessing the indicator reliability of each variable is the factor loading. This value represents the explanatory power of the indicator for the corresponding variable. The squared factor loading represents communality, which indicates the proportion of variance in an indicator explained by the corresponding variable. To meet the communality threshold of 0.5, the factor loading should be at least 0.7 (Comrey & Lee, 1992). Therefore, when the factor loading is 0.7 or higher, the indicator is considered to adequately reflect the actual characteristics of the corresponding variable and to possess sufficient explanatory power. The findings of this study indicate that most indicators met the threshold of a factor loading of 0.7 or higher, confirming that each variable was measured with reliability. However, one indicator within the Social Influence variable fell below 0.7, failing to meet the criterion. This result may be attributed to the inherent difficulty in subjectively assessing social influence. Despite this limitation, the Social Influence variable was retained in the analysis rather than being excluded. 〈Table 3〉 These findings suggest the need for supplementary approaches, such as additional survey design or in-depth interviews, to address the limitations observed in specific variables. Furthermore, a reassessment of the measurement method for the Social Influence variable appears to be a critical consideration for future research.

Table 3. Verification of Loading Values

Measurement Variable	Loading	Verification
Price Efficiency 1	0.9365	Accept
Price Efficiency 2	0.8817	Accept
Social Influence 1	0.5779	Reject
Social Influence 2	0.9872	Accept
Associated Experience 1	0.9634	Accept
Associated Experience 2	0.9896	Accept
Perceived Ease of Use 1	0.9354	Accept
Perceived Ease of Use 2	0.9338	Accept
Perceived Usefulness 1	0.9588	Accept
Perceived Usefulness 2	0.9636	Accept
Intention of Use 1	0.9709	Accept
Intention of Use 2	0.9676	Accept

4.2.2 Convergent Validity

Convergent validity is an indicator that assesses whether each variable has sufficient explanatory power for its corresponding construct. To evaluate this, Average Variance Extracted (AVE) was used. AVE represents the explanatory power of each variable, and a value of 0.5 or higher is generally considered to indicate sufficient convergent validity. In this study, the AVE values for all variables exceeded 0.5, confirming that each variable demonstrates high convergent validity. These results indicate that the variables used in this study accurately reflect their intended constructs. The AVE values are presented in 〈Table 4〉. Furthermore, the establishment of convergent validity serves as a crucial basis for ensuring the reliability of the proposed model.

Table 4. Results of Average Variance racted

Variable	AVE
Price Efficiency	0.827
Social Influence	0.654
Associated Experience	0.953
Perceived Ease of Use	0.873
Perceived Usefulness	0.923
Intention of Use	0.939

4.2.3 Discriminant Validity

Discriminant validity assesses whether each variable is clearly distinguishable from other variables and was verified using cross loadings. According to the Fornell-Larcker criterion, each variable should exhibit a stronger loading on its own construct than on any other constructs. In this study, the cross-loading analysis confirmed that most variables met the criterion. However, two items within the Social Influence variable showed values of 0.26 and 0.50, falling below the threshold. This suggests that these items do not exhibit clear differentiation from other variables, likely due to ambiguity in measuring social influence. Thus, while the overall discriminant validity assessment demonstrates strong validity, further refinement of the Social Influence variable is necessary.

The R^2 model fit index assesses how well the model corresponds to the given data, typically ranging from 0 to 1. A value closer to 1 indicates that the model more effectively explains the variability of the dependent variable, while higher correlations enhance the model's explanatory power. In the social sciences, a threshold of approximately 0.3 is commonly used to evaluate model fit. Cohen (1998) established benchmarks for effect sizes, defining 0.02 as a small effect size, 0.13 as a medium effect size, and 0.26 as a large effect size. Detailed classifications of these benchmarks are provided in 〈Table 5〉. These benchmarks serve as crucial reference points for model evaluation and interpretation.

Table 5. Criteria of R Square Values

Size of effect	% of Variance
Small	2
Medium	13
Large	26

The analysis results indicate that the explanatory power of the derived variables exceeded 0.3, demonstrating a meaningful level of explanation. Furthermore, as shown in 〈Table 6〉, all R^2 values of the estimated variables surpassed 0.5, indicating a highly robust model fit.

Table 6. Results of R Squared Values

Variable	R^2
Perceived Ease of Use	0.520
Perceived Usefulness	0.567
Intention of Use	0.746

4.3 Hypothesis Testing

This study expands the traditional Technology Acceptance Model (TAM) by incorporating validated variables to develop an extended research model, which was subsequently analyzed and statistically tested. The analysis produced path coefficients for each variable, with the results presented in 〈Table 7〉 and 〈Fig. 1〉. Based on these findings, a comprehensive evaluation of the influence of each variable was conducted, and the interrelationships among key variables were examined.

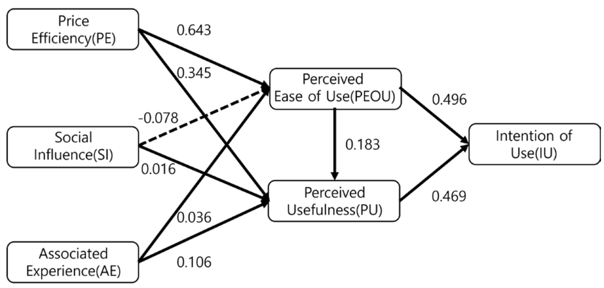

Fig. 1. Research Model with Path Coefficient

Table 7. Data of Cross Loading

Measurement Variable	PE	SI	AE	PEOU	PU	UI
Price Efficiency 1	0.93650586	0.4415761	-0.12200691	0.72740470	0.67625714	0.69898784
Price Efficiency 2	0.88171343	0.4908104	0.07495330	0.52942831	0.51383724	0.41813861
Social Influence 1	0.26333428	0.26333428	0.03542139	0.08723217	0.06862310	0.08643326
Social Influence 2	0.50582886	0.50582886	0.18096820	0.35094570	0.44703433	0.44955402
Associated Experience 1	-0.08686574	-0.08686574	0.96337452	-0.03022462	0.02099798	-0.07486511
Associated Experience 2	-0.01612243	-0.01612243	0.98958398	-0.01510917	0.08030708	-0.05585654
Perceived Ease of Use 1	0.66009860	0.66009860	-0.0435294	0.93540694	0.55001524	0.68540450
Perceived Ease of Use 2	0.65607678	0.65607678	0.00495031	0.93377157	0.57506728	0.77003018
Perceived Usefulness 1	0.61673655	0.61673655	0.05094840	0.55127827	0.95875102	0.70522906
Perceived Usefulness 2	0.65993198	0.65993198	0.06545376	0.60413166	0.96364849	0.76879908
Intention of Use 1	0.63817293	0.63817293	-0.08784282	0.77493487	0.76317836	0.97094712
Intention of Use 2	0.59026625	0.59026625	-0.03428027	0.73288020	0.72408283	0.96756493

4.3.1 Price Efficiency

The path coefficient from PE to PEOU was 0.643, the highest among all relationships, indicating that price efficiency has a significant impact on perceived ease of use. In other words, the higher the perceived price efficiency, the easier users find the technology to use. Additionally, the path coefficient from PE to PU was 0.345, confirming that price efficiency also positively influences perceived usefulness. This implies that when price efficiency is perceived as high, users are more inclined to regard the technology as useful.

4.3.2 Social Influence

An analysis of the impact of SI on PEOU and PU revealed that the path coefficient from SI to PEOU was -0.078, making it the only negative value observed. This suggests that as social influence, such as pressure or expectations, increases, users perceive the technology as less easy to use. In contrast, the path coefficient from SI to PU was 0.016, indicating that social influence has little to no impact on perceived usefulness. These findings imply that while social influence does not significantly affect perceptions of a technology's usefulness, it may exert a more negative influence on perceptions of ease of use.

4.3.3 Associated Experience

The path coefficient from AE to PEOU was 0.036, while the path coefficient from AE to PU was 0.106. This indicates that associated experience exerts a positive influence on both perceived ease of use and perceived usefulness, though its effect remains relatively minor. These findings suggest that while users' past experiences contribute to their perception of a new technology's ease of use and usefulness, they do not play a decisive role in its adoption.

4.3.4 Perceived Ease of Use

The path coefficient from PEOU to PU was 0.183, indicating that the easier a technology is perceived to use, the more likely it is to be considered useful. Additionally, the path coefficient from PEOU to IU was 0.469, suggesting that higher perceived ease of use strengthens users' intention to adopt the technology. These findings highlight that perceived ease of use serves as a critical determinant influencing both perceived usefulness and intention to use in the technology adoption process.

4.3.5 Perceived Usefulness

The path coefficient from PU to IU was 0.469, indicating that the more useful a technology is perceived to be, the stronger the intention to use it. This suggests that when a technology is recognized as delivering tangible value to users, their intention to adopt it increases significantly.

4.3.6 Intention of Use

Both PEOU and PU were found to have a positive impact on IU, indicating that the higher the perceived ease of use and usefulness of a technology, the stronger the intention to adopt it. These findings highlight the critical role of enhancing ease of use and perceived usefulness in fostering technology adoption. Therefore, it is essential to implement strategies that optimize user experience and provide tangible value throughout the technology development and adoption process. The results are summarized in 〈Table 8〉.

Table 8. Results of Path Coefficient

Variable	Path Coefficient
Price Efficiency → Perceived Ease of Use	0.643(+)
Price Efficiency → Perceived Usefulness	0.345(+)
Social Influence → Perceived Ease of Use	-0.078(-)
Social Influence → Perceived Usefulness	0.016(+)
Associated Experience → Perceived Ease of Use	0.036(+)
Associated Experience → Perceived Usefulness	0.106(+)
Perceived Ease of Use → Perceived Usefulness	0.183(+)
Perceived Ease of Use → Intention of Use	0.496(+)
Perceived Usefulness → Intention of Use	0.469(+)

4.4 Additional Survey Analysis

In addition to questions related to TAM variables, supplementary questions were included to further examine respondents' perceptions of computer vision-based object recognition technology. Notably, the results of a direct investigation into barriers to technology adoption, presented in 〈Table 9〉, align with the findings of the path coefficient analysis, where price efficiency exhibited the highest value. This suggests that the model used in this study effectively reflects real-world conditions. Therefore, when making decisions regarding the adoption of computer vision-based object recognition technology, prioritizing cost considerations appears to be a rational approach. These findings highlight the need to place a strong emphasis on cost efficiency when formulating technology adoption strategies.

Table 9. Direct Causes of Technology Adoption Barrier

Category	Count	Ratio
Excessive cost of technology adoption	23	35.9%
Uncertain technology effectiveness	22	34.4%
Difficulties in the technology adoption process	12	18.8%
Lack of skilled personnel	3	4.7%
Resistance to adoption from site personnel	3	4.7%
Ambiguous laws and regulations	1	1.6%
Challenges in technology maintenance and repair	0	0%

Table 10. Priority Areas of Technology Application

Category	Count	Ratio
Recognition of personal protective equipment usage	27	42.2%
Hazardous object recognition	16	25%
Recognition of hazardous areas (e.g., openings)	13	20.3%
Recognition of heavy and construction equipment	8	12.5%

The results regarding the priority of implementation in construction sites are presented in 〈Table 10〉, with the recognition of personal protective equipment (PPE) usage ranking the highest at 42.2%. Therefore, if computer vision-based object recognition technology is introduced in construction sites, prioritizing its application for PPE usage recognition would be the most appropriate approach. Assuming that the government leads the implementation of support programs for technology adoption, a survey was conducted to assess respondents' preferred support mechanisms. The results are presented in 〈Table 11〉.

Table 11. Preferred Government Support Policies

Category	Count	Ratio
Financial support for adoption costs	24	37.5%
Selection and operation of pilot sites	19	29.7%
Object recognition software and equipment rental	15	23.4%
Customized consulting support for companies	4	6.3%
Others	2	3.2%

The survey findings indicate that financial support was the most preferred method for technology adoption, suggesting that users are particularly sensitive to costs associated with the adoption process. To facilitate the widespread adoption of computer vision-based object recognition technology in construction sites, it is crucial for the government to prioritize financial support measures during the technology adoption process.

5. Conclusion

Despite the rapid global advancement of artificial intelligence and computer vision technologies, their adoption in construction sites remains limited. This study aimed to analyze this issue through a survey-based approach. Computer vision-based object recognition technology holds significant potential for accident prevention by enabling real-time monitoring of workers' actions and detecting hazards. However, its application is currently restricted to a limited number of construction sites. This limitation is likely due to various constraints arising during the adoption and implementation process. Accordingly, this study focused on identifying these barriers through a structured survey analysis.

Notably, this study was designed based on the Technology Acceptance Model (TAM) and incorporated six key variables for analysis: perceived usefulness, perceived ease of use, social influence, price efficiency, associated experience, and intention to use. User perceptions of computer vision technology were collected through a survey and quantitatively analyzed using the plspm library in R. Through this process, the relationships among variables, as well as the reliability and validity of the hypotheses, were systematically verified. The findings indicate that users are most sensitive to the cost of technology adoption, with price efficiency exerting the strongest influence on adoption intention. Conversely, social influence was found to have a negative impact on perceived ease of use, suggesting that as social pressure or expectations increase, users may perceive the technology as more difficult to use.

The direct analysis of constraints identified the high cost of technology adoption as the most significant barrier. This finding aligns with the results of the research model, underscoring the urgent need for measures to mitigate financial burdens and promote technology adoption. Furthermore, the study identified the monitoring of personal protective equipment (PPE) usage as the priority application area for computer vision-based object recognition technology in construction sites. This emphasizes the critical role of computer vision technology in enhancing worker safety and preventing accidents. Moreover, the findings highlight the necessity of institutional support, such as government-funded financial assistance, to ensure the successful and widespread adoption of this technology.

This study holds significant academic and practical implications as it systematically analyzes the factors contributing to the low adoption rate of computer vision-based object recognition technology in construction sites and provides empirical findings based on user perception data. Notably, it distinguishes itself by quantitatively addressing the issue of technology adoption, which has thus far remained largely theoretical, and by offering concrete policy recommendations for practical implementation. However, this study has certain limitations, including a relatively small sample size and the exclusion of potential variables beyond the TAM model. To address these limitations, future research should expand the sample size and incorporate diverse analytical approaches, such as case studies and field observations, to strengthen the reliability and validity of the findings.

In conclusion, this study systematically analyzed the key barriers to the adoption of computer vision-based object recognition technology in construction sites and underscored the critical role of policy support in facilitating technology implementation and enhancing workplace safety. These findings are expected to offer valuable insights for the future adoption and advancement of safety technologies in the construction industry, contributing to both technological innovation and accident prevention.

Acknowledgements

This study was partially supported by the National Research Foundation of Korea (NRF) with funding from the Ministry of Science and ICT (No. RS-2023-00218875). The authors would also like to thank Subin Choi, Undergraduate Research Assistant at the Kumoh National Institute of Technology Construction Engineering & Management Lab (KITCEM), for his assistance with English translation.

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