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The Adoption Intentions of Wearable Technology for Construction Safety

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Abstract: Wearable technology (WT) is vital for proactive safety management. However, the adoption and use of WTs are very low when it comes to construction safety. This study proposes a hybrid model, combining elements of the technology acceptance model and the theory of planned behaviour model, with the aim of determining the factors predicting the adoption intention of WTs for construction safety. A mixed-method approach was used to test the model, namely the structural equation model (SEM) and fuzzy-set qualitative comparative analysis (fsQCA). The results show that no single predictor can significantly drive the adoption intention of all six WTs, namely smart wearable sensors, smart safety hats, smart safety vests, smart insoles, smart safety glasses, and smart wristbands, except for the uncovered effective combinations based on each WT individually. This research contributes to new insights into the antecedents of the adoption intention of WTs for construction safety, which are also useful for other technologies.

Keywords: wearable technology; construction safety; adoption intention; mixed method; effective combinations; Australia

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1. Introduction

Construction sites are high-risk environments due to the various environmental risks, high physical demand, and constantly changing site conditions [1–3]. Despite increased efforts to improve the industry's dismal safety record, mortality and injury rates in the global construction industry remain high [4]. Safety management has a reputation for being passive, as it primarily responds to problems after they have occurred [4]. Current safety hazard identification procedures, such as site inspections, incident reports, and ticking off safety checklists, rely heavily on expert opinions to identify dangers [5], making safety management vulnerable to errors. As a result, many academics and practitioners have paid more attention to using emerging technologies in safety-critical systems in order to improve safety and operator performance [6,7].

Wearable technology (WT) is one of the most effective means for proactive safety management. WTs can be described as a category of electronic devices that are either worn directly on the body or incorporated into clothing, fashion accessories, and other everyday items [8], which are also known as "wearables", "wearable devices", and "wearable sensing devices". WTs generally have two functions: a form of communication that allows access to real-time information and the capacity for data input with local storage. Therefore, WTs have the potential to transform conventional practices in construction projects by capturing and managing information, thereby improving safety in the construction industry. As technology adoption is the beginning stage of any business [9], and an emerging WT that is not embraced by its targeted users will never be a success, decision-makers or managers should understand the factors that influence users' decisions to use a particular WT, especially in the early development and diffusion stages. Thus, to achieve the goal of

WTs to be effectively utilized in construction safety management, the key factors influencing the adoption intentions of WTs in the construction industry need to be investigated.

Although WTs provide a positive prospect in safety management, WTs are still not applied as a routine tool in the construction industry. Previous research has either proposed a conceptual framework [10,11] or assessed the benefits and challenges of WTs [4]. More than that, previous studies focus on limited types of WTs, such as wristbands [12], smart vests [13], or wearable sensing devices [14], rather than providing a comprehensive list of market-ready WTs. The functions and properties of WTs differ significantly, so the influential factors may vary among WTs [15]. As such, it is essential to provide a holistic view to effectively better comprehend the influential factors of various WTs' adoption intentions for construction safety. Moreover, from the methodological perspective, prior empirical studies on WTs adopted partial least squares (PLS) [16,17] and multiple linear regression [13], which might lead to over-simplification due to the only consideration being of path coefficients. On the contrary, the use of WTs is still quite limited in the construction industry; thus, the data collected most likely are not normally distributed. Such symmetrical approaches may yield inaccurate effects [18], as they cannot explain the complex configurations.

To fill these gaps, first, the updated market-ready WTs were selected to maximise the replication of the real-world decision-making process. Second, this study also attempted to integrate components of the technology acceptance model (TAM) and the theory of planned behaviour (TPB) to thoroughly measure the factors driving the adoption intention of various WTs because of their capability to investigate internal and external factors affecting the adoption intention. Third, a mixed-method approach of the SEM-fsQCA was employed to explore and determine the number of effective combinations of the factors based on the complex substances. The research findings would provide a new understanding of the required determinants and pathways for adopting WTs for construction safety. This research would also contribute to the promotion and effective use of other advanced technologies in the construction industry through the uncovered effective combinations and insightful references from WTs.

2. Conceptual Background

2.1. Wearable Technologies for Improving Construction Workers' Safety

As WTs have gained traction globally, various studies have extensively demonstrated the benefits of WTs in enhancing efficiency at work, monitoring fitness levels, increasing workplace safety, and even saving lives across industries such as healthcare, manufacturing, mining, and athletics [1,19–22]. More recently, WTs have drawn attention in the construction industry to identify safety hazards, especially within workforces engaging in high-risk activities in dangerous working environments [1,4,5]. These studies revealed that WTs have the potential to provide real-time, more accurate, and accessible data to enable action to be taken faster and more effectively to address safety risks.

Generally, WTs used in safety management are intrusive. They usually need indirect forms of attachment like belts, straps, and tags, preventing the detachment of mobile devices from the body when performing a given task [5,23]. Several studies have evaluated safety management using WTs in construction operations [1,3,24]. The top six market-ready WTs in the current study were selected and are summarised in Table 1. This study has excluded WTs that are still in the development stage (e.g., exoskeletons) after considering the wearable device's durability and the cost–benefit ratio, which often requires more training and some form of larger platform to work properly.

Table 1. WTs' types and functions.

Technologies	Functions	References
Wearable Sensor Tags (T) Small, lightweight devices embedded with sensors that can be worn on items of clothing or accessories, e.g., Spot-R Clip, Triax Tech.	Location tracking Incident alert Evacuation alarm Access card Social distancing Proximity alerts	[1,4,25]
Smart Hard Hats (H) A traditional rigid helmet worn to protect the head with integrated sensors, e.g., CATdetect, CAT and Life Wearable, SmartCap.	Location tracking Proximity alerts Fatigue monitoring	[4,19,26–28]
Smart Safety Vests (V) A standard high-visibility vest with integrated sensors, e.g., Smart Safety Vest, Redpoint.	Location tracking Proximity alerts Posture tracking Social distancing	[4,13,19,23,26,29,30]
Smart Insoles (I) Insoles designed with embedded sensors that can be inserted into footwear, e.g., Smart Insoles, Zhor Tech.	Detect falls on the same level Location tracking Posture alerts	[5,31–33]
Smart Safety Glasses (G) Glasses with a built-in computer that displays information and alerts on the lenses over the real-world perception, e.g., Smart Glasses, XOEye and Vuzix.	Virtual display Proximity alerts Location tracking	[4,19,34–36]
Smart Wristbands (W) A band worn around the wrist with sensors embedded, e.g., off-the-shelf products.	Physiological monitoring Assesses physical demand Location tracking	[1,4,12,13,19,37]

2.2. Technology Acceptance Model and Theory of Planned Behaviour Model

The TAM, proposed by Davis (1989) [38], is widely regarded as one of the most influential theoretical models in the acceptance and usage of a technology based on users' perceptions. The TAM posits that users' perceived utility (PU) and perceived ease of use (PEoU) are pivotal factors shaping their acceptance and utilisation of that technology. In the construction industry context, the TAM has been extensively used to explain users' acceptance of emerging technologies. For example, Wong et al. (2021) [39] explored construction workers' acceptance of personal protective equipment through the TAM. Zhang et al. (2022) [40] investigated the factors behind the low acceptance of virtual reality based on an extended TAM. These studies indicate that the TAM plays an impactful role in analysing the adoption intention of WTs. Therefore, by referring to the TAM, construction personnel's motivation in their decision making can provide useful insights into understanding the adoption intentions of WTs for construction safety.

The TPB model was initially put forward by Ajzen (1991) [41]. It has since then become one of the most popular and widely used theories in investigating human behaviours, in which people have the ability to exert self-control. The TPB model contends that the behaviour of a person can be predicted with the help of behavioural intention, which again depends on three determinants—Attitude (Att), subjective norms (SNs), and perceived behavioural control (PBC). Over the past few years, TPB has been extensively used as a fundamental theory for construction workers' behaviour intentions. Peng and Chan (2019) [42] used the TPB as the basic model to predict the safety compliance behaviours of older construction workers. Yang et al. (2017) [43] explained customers' behaviour intentions to adopt and use smart home services by extending the TPB model. Okpala et al. (2021) [16] examined the relationships between several key technology acceptance variables in the context of wearable sensing devices in the construction industry by using the TPB as one of the basic theories. The validity of the TPB model in explaining the adoption intention of WTs in the construction industry has been validated in the above studies.

2.3. Conceptual Model

The TAM and TPB are widely used in diverse fields to ascertain the acceptance of emerging technologies. The TAM and TPB originated from the ideas of the theory of reasoned action by Ajzen and Fishbein (1977) [44], making it possible for the two models to be integrated. An integrated model of the TAM and TPB investigates both internal and external factors, enabling better explanatory and predictive utilities in the adoption intention of WTs [45]. Furthermore, several studies have identified perceived privacy security (PPS) as an influential factor, as a higher perceived privacy risk tends to lead towards lower levels of adoption intention [13]. Similarly, when workers use wearable technologies, there is a perception of risk involved in transmitting sensitive information. Hence, this study also attempts to expand the integrated model of the TPB and TAM based on PPS as an additional construct to enhance the explanatory power. The conceptual model is depicted in Figure 1.

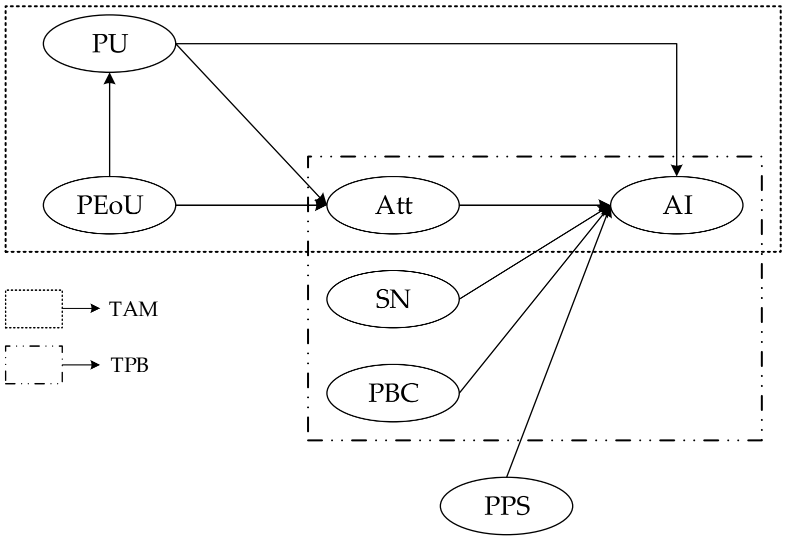

Figure 1. Conceptual model.

3. Hypothesis Development

3.1. Perceived Utility

Davis (1989) [38] proposed the TAM, which explains the user acceptance and usage of a technology based on user perceptions. According to the TAM, workers must have perceived utility (PU) and perceived ease of use (PEoU) in the decision making on whether to adopt wearable technologies, which would influence their attitude toward using WTs. PU is defined as the extent to which an individual believes that implementing a specific system would enhance their job performance [38]. In the context of wearable technologies, PU gauges workers' confidence in a WT's ability to contribute to their job performance and safety. If the technology is perceived to augment task performance, the inclination to adopt the technology will increase. Therefore, we posit the following:

H1. *PU will have a positive influence on the adoption intention of WTs.*

3.2. Perceived Ease of Use

PEoU is defined as the extent to which an individual believes that utilizing a specific system would require minimal effort [38]. Contemporary wearable technologies are purposefully crafted with user-friendliness in mind, featuring generally intuitive and easy-to-navigate interfaces. This design approach enhances workers' confidence and fosters positive attitudes toward wearable technologies. Also, it is crucial to balance the value added by wearable technologies with the imperative not to escalate the effort required to perform tasks, as an increase in task effort may diminish the intention to adopt the proposed technology. Moreover, several studies have verified that construction workers could perceive specific technology or equipment as being more useful if it was easier for them to comply with the procedures suggested [46,47]. The PEoU of WTs indicates that such technologies are easily understood and user-friendly, without the need for training, enabling workers to overcome the uncertainty and disadvantages of WTs and facilitate their perceived usefulness and, thus, intention to use them [13,48]. Therefore, we posit the following:

H2. *PEoU will have a positive influence on the adoption intention of WTs.*

H3. *PEoU will have a positive influence on the PU of WTs.*

3.3. Attitude

Att is defined as an individual's positive or negative feelings about performing the target behaviour [49]. Att is utilized as a predictor of behavioural intention, leveraging its established impact on behavioural intentions in prior studies [13]. In the context of this study, Att assesses workers' attitudes and emotions regarding the use of WTs. A positive attitude toward a specific wearable technology is expected to enhance the intention to adopt it, while strong negative feelings may have the opposite effect. Furthermore, attitude was found to be a significant mediator in the TAM and is important in predicting intentions to adopt new technologies in general [50]. From the perspective of this investigation, if WTs are simple to comprehend or easy to use, construction workers are more inclined to perceive their convenience and usefulness and develop a positive attitude toward the WTs. Therefore, we propose the following hypotheses:

H4. *Att will have a positive influence on the adoption intention of WTs.*

H5. *PU will have a positive influence on Atts towards WTs.*

H6. *PEoU will have a positive influence on Atts towards WTs.*

3.4. Social Norms

SNs have been defined as an individual's reaction to social preferences for performing a particular behaviour [51]. SNs have been demonstrated to significantly and positively influence the adoption intentions of new technologies across various fields [52]. In the construction sector, a highly coordinated work environment with numerous workers engaged in various activities, communication and engagement with others is pivotal. Additionally, SNs play a crucial role in the early stages of innovation implementation, as individuals often act based on their perception of others' expectations [50]. Hence, we propose the following:

H7. *SNs will have a positive influence on the adoption intention of WTs.*

3.5. Perceived Behavioural Control

PBC, as defined by the perceived ease or difficulty of performing a behaviour, hinges on the belief in possessing the necessary resources, opportunities, and ability [41]. PBC plays a pivotal role in utilizing technology or adopting new technologies [50]. An increase in PBC, signifying workers' belief in having the necessary control and resources to adopt WTs, enhances the likelihood of expressing a positive intention to do so. Conversely, if perceiving the required behaviour as difficult, the intention to adopt is likely to decrease. Therefore, we posit that:

H8. *PBC will have a positive influence on the adoption intention of WTs.*

3.6. Perceived Privacy Security

PPS is defined as an individual's willingness to share their personal data with others, given the likelihood of potential privacy harm [53]. Privacy and security issues, which have emerged across various sectors in the field of information technology, constitute the core problems impeding technology adoption and dissemination [54]. Quite a few studies have confirmed that privacy risk is strongly associated with adoption intention levels, especially for WT products [54,55]. WTs compound and amplify privacy risks in the mobile environment by gathering additional and intimate personal information. As a result, when risk perception is high, there is a higher possibility of forming an adverse attitudinal perception and intention toward using WTs. On the contrary, the higher the level of PPS, the higher the adoption intention. Therefore, the following hypothesis is proposed:

H9. *PPS will have a positive influence on the adoption intention of WTs.*

4. Methodology

Considering the time and cost restraints, this research adopted a cross-sectional correlational strategy to investigate various correlations between variables at a single time point [47]. This study evaluated participants' perceptions using a self-reporting tool to establish their intention to adopt various WTs.

4.1. Data Collection and Procedure

Qualtrics (https://www.qualtrics.com) is a cloud-based platform designed for collecting, analysing, and acting on data for various research and feedback purposes, establishing itself as a pivotal choice for researchers worldwide. Given that this study was conducted during the COVID-19 lockdown and the survey population consisted of all construction workers in companies implementing new innovative technology in Australia, a sampling frame was unavailable. Consequently, convenience sampling was employed to recruit participants. The participants were recruited through flyers and email correspondence featuring a QR code and a link to the Qualtrics-created questionnaire between 20 July 2021 and 30 November 2021. The study targeted Tier 1/2 construction companies in Western Australia, considering their potential funding and resources for implementing new innovative technology. Successful technology adoption necessitates both a top-down and bottom-up approach [56]. In this context, two key personnel groups directly influencing technology adoption are management staff and field workers. Management staff serve as drivers and facilitators, while field workers are directly influenced by new technology. Therefore, both groups were surveyed.

Several measures were implemented to ensure correct and accurate participant responses:

(1) Participant responses were handled anonymously, and participants were explicitly informed that their responses would not be assessed for accuracy, with determinations of correctness or incorrectness provided;
(2) The research objective and survey process were comprehensively introduced, including detailed explanations presented in six WTs, accompanied by figures and videos. Participants were then requested to voluntarily respond based on their impression or understanding of each technology;
(3) Recognizing that technology adoption is primarily influenced by the function of the technology, participants were specifically instructed to answer questions related to the location-tracking function of each technology.

Following the exclusion of incomplete, inconsistent, and inaccurate responses, a total of 84 valid responses were obtained, qualifying the minimum sample size suggested by Hair et al. (2011) [57]. Table 2 provides a summary of the demographic information of the respondents.

Table 2. Demographics of participants.

Characteristics	Number	Percentage
Age		
≤29 years	22	26.2%
30–39 years	31	36.9%
40–49 years	15	17.9%
≥50 years	16	19.0%
Work Experience		
0–5 years	17	20.2%
6–16 years	34	40.5%
16–25 years	19	22.6%
≥26 years	14	16.7%
Experience with WTs		
Yes	20	23.8%
No	64	76.2%

4.2. Survey Instruments and Measurements

The measurements adopted in this study were based on the existing measurement scales that have been validated and reviewed in the related literature (See Appendix A for detailed measurements). PU, PEoU, SNs, and adoption intention were adapted from the scales of Choi et al. (2017) [13], consisting of a total of 15 items, three each for the five constructs. To measure Att and PBC, two three-item measures were modified from the scales developed by Okpala et al. (2021) [17]. PPS was adapted from Roca et al. (2009) [58]. All items were designed with reference to a 5-point Likert scale. In addition, this study would examine the demographics of participants involved in safety management as control variables, namely their age and working experience.

4.3. Data Analysis

A combination of the PLS-SEM and fsQCA approaches were used in each study. As WTs are still relatively new to the construction industry, the sample size and the number of market-ready WTs that could be used for research were limited. PLS-SEM is renowned for its robustness with small samples, particularly in comparison to other structural equation modelling techniques. Given the exploratory nature of this study and the non-normal distribution of the data utilized [59], PLS-SEM was selected over covariance-based structural equation modelling tools. This research employed the SmartPLS v3.2.6 software to conduct the PLS-SEM for symmetrical analysis, following a two-step procedure proposed by Hair et al. (2019) [59]. Although SEM could examine the impact of antecedents on outcome variables in isolation from each other, which is a net effects analysis, there are few insights into whether one, all or combinations of these antecedents have effects on outcome variables. On the other hand, fsQCA allows for a nuanced analysis of cases and provides insights into the multiple pathways leading to a specific outcome. In other words, fsQCA is an asymmetric approach, focused on capturing the complex, non-linear relationships between conditions and outcomes. Therefore, it was utilized as a complementary approach to determine the combined effect of the causal factors asymmetrically, following the procedure suggested by Ragin (2009) [60].

5. Results

This study was applied to six contexts, including wearable sensor tags (Study T), smart hard hats (Study H), smart safety vests (Study V), smart insoles (Study I), smart safety glasses (Study G), and smart wristbands (Study W).

5.1. Findings from the Symmetrical Analysis (PLS-SEM)

A pre-test was performed before conducting the formal analysis. According to the results of the exploratory factor analysis, Att_3 and PBC_1 were removed in the final analysis as they did not load onto the expected conceptual factor. Thus, 19 items were retained in the final SEM analysis.

5.1.1. Measurement Model

Cronbach's alpha, rho_A, composite reliability (CR), factor loadings, and average variance extracted (AVE) were used to assess the measurement model's reliability and validity. Appendix A summarizes the findings. Most Cronbach's alpha and CR values exceed the 0.8 limit [61]. Although the Cronbach's alpha of PBC in Studies H and V did not exceed the threshold of 0.7, the values of Dijkstra–Henseler's rho (pA) exceeded the recommended threshold of 0.7, as proposed by Henseler et al. (2016) [62]. Rho_A is a substitute for the classic Cronbach's alpha and the more liberal composite reliability. All of this indicates a high level of trustworthiness. Standard factor loadings and AVE analysis were used to determine convergent validity. All item loadings were significant and greater than 0.6, indicating acceptable convergent validity. As a result, all AVE ratings exceeded the recommended 0.5 criterion [61]. The square root of the AVE for each construct was substantial, implying sufficient discriminant validity. The path coefficient values for the control variables were less than 0.2 and non-significant, indicating that none of the control variables was significant.

Regarding the common method variance (CMV) issue, several procedural methods have been conducted to mitigate it before data collection. First, to ensure that respondents had significant levels of knowledge regarding the WT mentioned in the question, the purpose of the survey and the detailed explanations of six WTs were provided with both figures and videos, which could reduce single-source bias. Second, their participation was anonymous and voluntary. To ensure that CMV is not an issue in the current study, the partial correlation method proposed by Podsakoff et al. (2003) [63] was conducted within the six WTs. According to the results, there was not much change in the R^2 (less than 10%), indicating that the issue of CMV was minimal.

5.1.2. Structural Model

The structural model is mainly assessed based on the coefficient of determination (R^2), predictive relevance (Q^2), and significance of path coefficients. The path coefficients and their significance were calculated via bootstrapping, aided by SmartPLS v3.2.6, based on the original cases and 5000 subsamples. The results of the structural model are converted to significance levels, i.e., p-values, as shown in Figure 2. The R^2 values for each context ranged from 0.560 to 0.795, which achieved a satisfactory level. All Q^2 values were above zero, implying the ability of the model to predict the adoption intention of various WTs in the construction industry. The results of the hypotheses are summarized in Table 3. H1 and H3 were supported in all six contexts, while H6 and H8 were not supported in all six contexts. H2 was supported in all cases except in Study H. H4 was not supported, except in Study W. H5 was supported in studies T, H, V, and G, but was not supported in studies I and W. H7 was not supported, except in Study I.

Table 3. Results of hypothesis testing.

	Study T		Study H		Study V		Study I		Study G		Study W	
	Beta	Result	Beta	Result	Beta	Result	Beta	Result	Beta	Result	Beta	Result
H1	0.474 ***	S	0.665 ***	S	0.587 ***	S	0.593 ***	S	0.756 ***	S	0.806 ***	S
H2	0.384 ***	S	0.159 N.S.	NS	0.499 ***	S	0.309 *	S	0.278 **	S	0.802 ***	S
H3	0.470 ***	S	0.712 ***	S	0.431 ***	S	0.660 ***	S	0.681 ***	S	0.681 ***	S
H4	−0.011 N.S.	NS	−0.120 N.S.	NS	0.194 N.S.	NS	0.178 N.S.	NS	0.297 N.S.	NS	0.559 *	S
H5	0.431 ***	S	0.485 *	S	0.674 ***	S	0.209 N.S.	NS	0.595 ***	S	0.310 N.S.	NS
H6	0.183 N.S.	NS	0.158 N.S.	NS	0.059 N.S.	NS	−0.122 N.S.	NS	−0.031 N.S.	NS	−0.120 N.S.	NS
H7	0.017 N.S.	NS	0.066 N.S.	NS	0.037 N.S.	NS	0.344 **	S	0.083 N.S.	NS	−0.163 N.S.	NS
H8	0.188 N.S.	NS	0.252 N.S.	NS	−0.078 N.S.	NS	0.108 N.S.	NS	0.017 N.S.	NS	0.041 N.S.	NS

Notes: Displayed values are coefficients; S means supported and NS means not supported; N.S. means not significant; * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

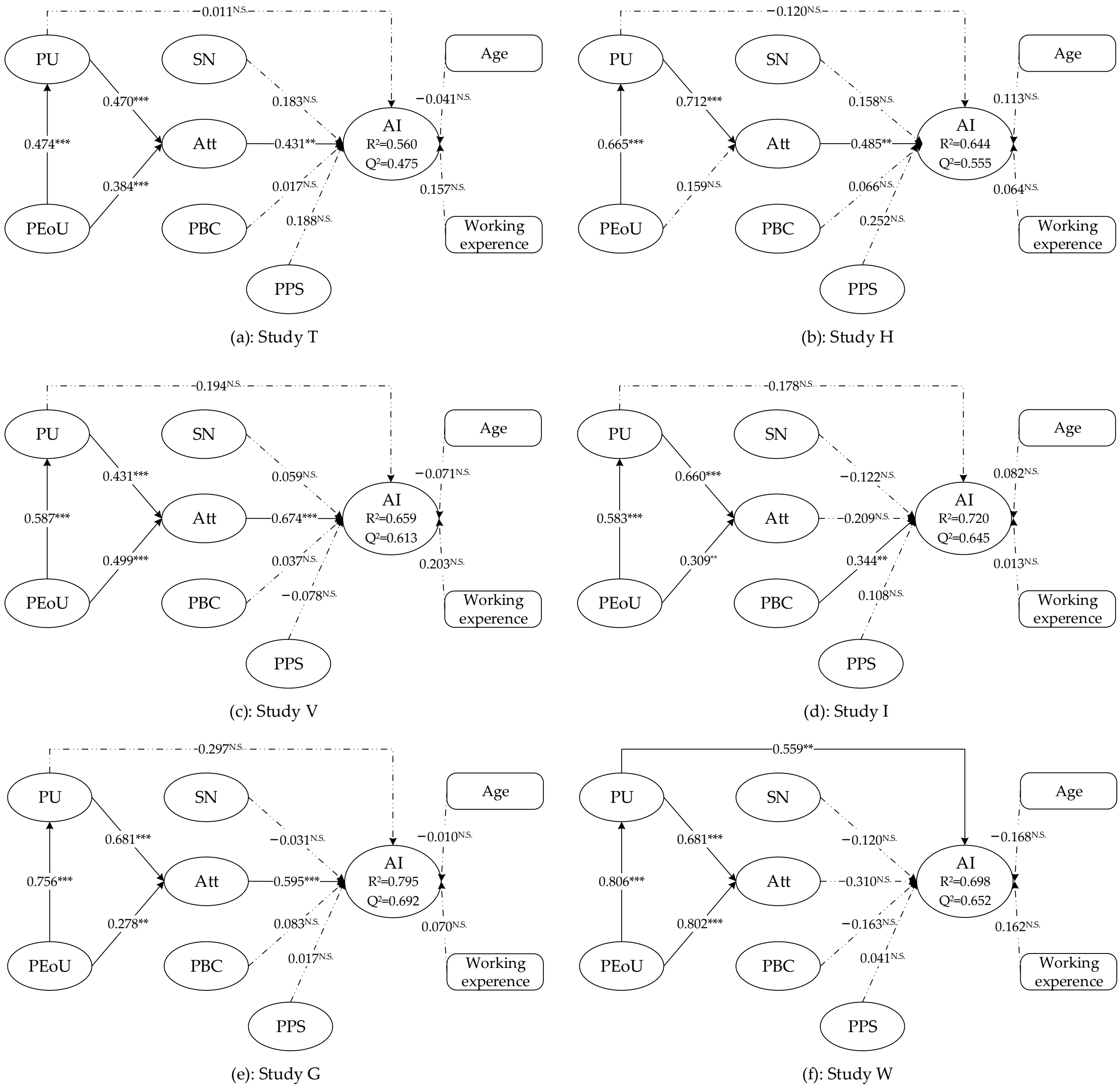

Figure 2. Structural model results. Note: AI = adoption intention; displayed values are coefficients; N.S. means not significant; ** $p < 0.01$. *** $p < 0.001$.

5.2. Findings from the Asymmetrical Analysis (fsQCA)

5.2.1. Calibration and True Table Construction

As QCA only works for data ranging from 0 to 1, calibration should be performed before conducting fsQCA. Considering that the variables were measured using five-point Likert scales, this study calibrated the raw data according to three qualitative breakpoints (2, 3 and 4) proposed by Pappas and Woodside (2021) [64]. For example, working experience of "≤5 years" was calibrated as "0", "6–16 years" was calibrated as "0.33", "16–25 years" was calibrated as "0.67", and "26 years" was calibrated as "1". For the role, "worker" was calibrated as "0", while "manager" was calibrated as "1".

5.2.2. Analysis of Necessary Conditions

Analysing necessary conditions involves identifying and understanding the essential prerequisites or factors that must be present for a particular event or outcome to occur. Necessity conditions analysis (NCA) represents the proportion of fuzzy set scores in a condition that is less than or equal to the corresponding scores in the outcome. When the consistency is $\geq$0.9, the individual conditions can be clarified as necessary conditions. The NCA results in Table 4 illustrate that there is no necessary condition for the adoption intention of all six WTs.

Table 4. Analysis of necessity.

Conditions Tested	Study T		Study H		Study V		Study I		Study G		Study W	
	CS *	CV *	CS *	CV *	CS *	CV *	CS *	CV *	CS *	CV *	CS *	CV *
PPS	0.462	0.893	0.580	0.879	0.529	0.864	0.614	0.928	0.596	0.937	0.557	0.968
~PPS	0.701	0.392	0.692	0.268	0.716	0.449	0.673	0.382	0.585	0.486	0.637	0.471
PU	0.633	0.773	0.616	0.762	0.581	0.909	0.762	0.893	0.802	0.960	0.719	0.978
~PU	0.626	0.421	0.692	0.284	0.676	0.431	0.581	0.370	0.426	0.423	0.496	0.415
PEoU	0.471	0.861	0.451	0.840	0.553	0.921	0.572	0.938	0.727	0.949	0.697	0.944
~PEoU	0.749	0.426	0.819	0.303	0.648	0.403	0.686	0.378	0.499	0.464	0.520	0.437
SN	0.742	0.816	0.653	0.803	0.687	0.902	0.756	0.842	0.748	0.938	0.719	0.931
~SN	0.574	0.411	0.731	0.301	0.590	0.408	0.588	0.385	0.491	0.471	0.513	0.443
Att	0.699	0.883	0.649	0.888	0.665	0.956	0.680	0.919	0.831	0.946	0.739	0.959
~Att	0.574	0.380	0.691	0.275	0.587	0.388	0.632	0.375	0.365	0.380	0.509	0.439
PBC	0.370	0.926	0.368	0.874	0.413	0.976	0.549	0.982	0.635	0.981	0.510	0.989
~PBC	0.826	0.433	0.898	0.318	0.781	0.438	0.687	0.368	0.585	0.490	0.676	0.478

Notes: "~" means logical operator NOT; "CS *" means consistency, "CV *" means coverage.

5.2.3. True Table Construction and Sufficiency Analysis

A truth table was generated using fsQCA, including all logical and plausible configurations of those conditions. Generally, consistency and coverage were used to assess the truth table. Consistency measures the extent to which a causal combination leads to an outcome, while coverage is used to measure the extent to which the outcome of interest may be explained by the configurations. Moreover, proportional reduction in inconsistency (PRI) was also used to avoid simultaneous subset relations of configurations in both the outcome and the absence of the outcome. Following the suggestions from Pappas and Woodside (2021) [64], this study used a frequency threshold of 1 (as samples < 100), a consistency threshold of 0.80, and a PRI consistency threshold of 0.75 to assess the truth table. Next, the antecedent condition configurations that had a certain degree of sufficiency for the adoption intention of various WTs were filtered out. The output of fsQCA consists of a complex solution (not using a logical remainder), a parsimonious solution (using both easy and challenging logical remainders to analyse the resulting configurations), and an intermediate solution (using the easy counterfactual analysis to create configurations, including core and edge conditions). Following suggestions from Pappas and Woodside (2021) [64], both parsimonious solutions and intermediate solutions were considered with the accepted consistency threshold of 0.8. The graphical solutions are summarised in Tables 5 and 6. According to Tables 5 and 6, no single predictor will cause the adoption intention of WTs in all six contexts; instead, multiple combinations will.

5.2.4. Robustness Tests

Following the suggestions of Fiss (2011) [65], we replicated the analyses with increased consistency thresholds (0.85) to test the stability of the solutions. There is little change from those presented in Table 4. Thus, it can be concluded that the results of the fsQCA analysis are stable.

Table 5. Configurations of Studies T, H, and V based on the intermediate and the parsimonious solutions.

	Study T			Study H		Study V		
	S1	**S2**	**S3**	**S1**	**S2**	**S1**	**S2**	**S3**
PU	•	•	•	•	•	⊗	⊗	•
PEoU	•		⊗	⊗	•	⊗	•	•
Att	•	•	•	•	•	•	•	•
SN	•	•	•	•	•	•	•	•
PBC		•	⊗	⊗	•	⊗	⊗	•
PPS	•	•	⊗	•	•	•	⊗	•
Raw Coverage	0.299	0.260	0.321	0.300	0.245	0.252	0.262	0.292
Unique Coverage	0.052	0.017	0.148	0.126	0.071	0.075	0.073	0.108
Consistent	0.973	0.972	0.913	1.000	1.000	0.993	0.993	1.000
Solution Coverage	0.485			0.371		0.451		
Solution Consistent	0.941			1.000		0.996		

Notes: • indicates the presence of a condition, and ⊗ indicates its absence; large circles mean core conditions while small circles mean peripheral conditions; blank spaces indicate that the corresponding causal condition plays an insignificant role in the configuration.

Table 6. Configurations of Studies I, G, and W based on the intermediate and the parsimonious solutions.

	Study I		Study G				Study W			
	S1	**S2**	**S1**	**S2**	**S3**	**S4**	**S1**	**S2**	**S3**	**S4**
PU	•	•	•	•	⊗	⊗	•	•	⊗	•
PEoU	⊗	•	•	•	⊗	⊗	•	•	⊗	•
Att	•	•	•	•	•	•	•	•	⊗	⊗
SN	•	•	•	•	⊗	•	•	•	⊗	⊗
PBC	•	•		•	•	•		•	⊗	⊗
PPS	⊗	•	⊗		•	⊗	•		•	⊗
Raw Coverage	0.274	0.378	0.268	0.511	0.154	0.198	0.453	0.463	0.195	0.224
Unique Coverage	0.053	0.157	0.043	0.285	0.018	0.020	0.029	0.033	0.057	0.057
Consistent	0.996	1.000	0.978	1.000	1.000	1.000	0.986	0.994	0.972	0.991
Solution Coverage	0.431		0.597				0.620			
Solution Consistent	0.998		0.990				0.978			

Notes: • indicates the presence of a condition, and ⊗ indicates its absence; large circles mean core conditions while small circles mean peripheral conditions; blank spaces indicate that the corresponding causal condition plays an insignificant role in the configuration.

5.3. *Effective Combinations from PLS-SEM and fsQCA*

The joint analyses from PLS-SEM and fsQCA render insightful references into the effective combinations of the factors in predicting the adoption intentions of WTs for construction safety. The following discussions focus on the detailed combinations for each WT.

In Study T, three causal configurations with high consistency (above 0.90) that contribute to the adoption intentions of wearable sensor tags have been reported. Among the three configurations, the combination of S2 offers the best representation of adoption intentions as it has the highest raw coverage (0.321). Alternatively, the combinations of S1 and S2 are more likely to be beneficial, as shown by a consistency score of 0.973 and 0.972. This solution is supported by 29.90% and 26.00% of the participants (raw coverage). Moreover, since PU and Att appear in both parsimonious and intermediate solutions, they are considered as core conditions for adoption intentions in Study T, a kind of hygiene factor whose absence often inhibits adoption intentions but whose sole presence cannot stimulate adoption. These findings are partly consistent with the PLS-SEM analysis, as Att has a positive effect on adoption intention. Although the significant direct effect of PU on adoption intention is not observed in the results of PLS-SEM, the fsQCA analysis results show that PU is a core condition, implying a strong relationship between PU and adoption intention. This finding can be explained by the significant effect of PU on Att combined with the significant effect of Att on adoption intention. This means that PU can indirectly affect the adoption intention through Att. However, PEoU also has a significant effect on Att, and it is just a peripheral element for facilitating the adoption intention of smart safety tags, implying a weaker relationship with adoption intention.

In Study H, two configurations that facilitate the adoption intention of smart safety hats are extracted, in which attributes are complementary or substituted. Although the significant effects of SNs and PPS were not supported in the SEM analysis, the fsQCA analysis paints a different story. According to Table 5, PPS, PU, SNs, and Att were the core conditions, indicating that the lack of these four factors will have a strong adverse impact on the adoption intention of smart safety hats, while the presence or absence of PEoU and PBC does not make a difference.

In Study V, the significant effect of SNs on the adoption intention is not observed in the PLS-SEM analysis; however, SNs are the causal core condition, implying that the lack of SNs has a very strong adverse impact on the adoption intention in the context of smart safety vests. Further, fsQCA analysis finds that there have been three substituted configurations contributing to the adoption intention of smart safety vests. Among the configurations, S3 offers the best representation of adoption intention, which means that this configuration accounts for 29.2% of the membership. This means that a combination of PU, PEoU, Att, SNs, PBC, and PPS will facilitate a high level of adoption intention for smart safety vests.

In Study I, two configurations have been identified through fsQCA analysis, in which S2 can represent more cases in this group as it has a higher raw coverage (0.378) than S1. S2 implies that the combination of all factors, including PU, PEoU, Att, SNs, PBC, and PPS, will lead to a high level of adoption intention for safety insoles. However, these findings contrast with the results of the PLS-SEM analysis, which found that none of the constructs significantly impact the adoption intention. Moreover, fsQCA analysis indicates that SNs, Att, and PBC were three core causal conditions for adoption intention, implying that if any of the three factors do not exist, it may cause a low adoption intention.

In Study G, although SNs and PBC did not significantly impact adoption intention according to the PLS-SEM analysis, there were four solutions for achieving high levels of adoption intention for smart safety glasses in the fsQCA analysis. Among these four solutions, S2 has the highest consistency and unique coverage, indicating that the combination of high levels of PU, PEoU, SNs, Att, and PBC mostly contributes to high levels of adoption intention. Moreover, Att, SNs, and PBC are core causal conditions for adoption intention in the context of smart glasses.

Overall, the fsQCA analysis revealed four configurations in Study W, with S2 receiving special attention due to its high consistency scores, raw coverage, and unique coverage. In S2, PU is the core condition for adoption intention in the context of smart wristbands, which is consistent with the findings obtained from the PLS-SEM analysis, as PU significantly impacts adoption intention. Also, S2 indicates that the combination of high levels of PU, PEoU, SNs, Att, and PBC mostly contributes to the high levels of adoption intention for smart wristbands. Further, PPS also constitutes an essential causal criterion for adoption intentions in the combined parsimonious solution with an intermediate solution, indicating that the lack of PPS will cause a low adoption intention for smart wristbands.

6. Conclusions and Discussions

This study examined the hybrid model from the integrated TAM and TPB models. The results of this mixed-method research found the effect of antecedent variables as well as effective combinations of factors driving the adoption intentions of WTs for construction safety. Although this study upholds the assertion that adoption intention is a complicated situation generally, the results of the fsQCA further clarified the complex trade-off effect of PU, PEoU, SNs, Att, PBC, and PPS than the SEM analysis. The results of the fsQCA indicated that there were core but not sufficient conditions for adoption intention, especially when the conditions were considered individually. To some extent, all six factors were necessary to facilitate adoption intention. For example, regarding Study T, three causal configurations with high consistency (above 0.90) that contribute to the adoption intention of wearable sensor tags have been reported. Among the three configurations, the combination of S2 offers the best representation of adoption intention as it has the highest raw coverage (0.321). These findings are partly consistent with the PLS-SEM analysis, as Att has a positive effect on adoption intention. Although the significant direct effect of PU on adoption intention is not observed in the results of the PLS-SEM, the fsQCA analysis results show that PU is a core condition, implying a strong relationship between PU and adoption intention. This finding can be explained by the significant effect of PU on Att combined with the significant effect of Att on adoption intention. This means that PU can indirectly affect the adoption intention through Att. However, PEoU also has a significant effect on Att, and it is just a peripheral element for facilitating the adoption intention of smart safety tags, implying a weaker relationship with adoption intention.

6.1. Theoretical Contributions

This research has two major theoretical contributions. First, it is the first investigation to systematically examine users' adoption intentions of WTs for construction safety based on a hybrid model combining the TAM and TPB models. Despite the preliminary acceptance of some WTs in the past [2], this work extends the existing research by revealing the effective combinations of factors affecting the adoption intention of each WT. Moreover, by considering the updated and more comprehensive WTs used in the construction industry, this study renders more contemporary insights into WTs for construction safety from the empirical context.

Second, this research makes a broader methodological contribution to the adoption intention of WTs in the construction industry through a mixed-method approach, namely SEM and fsQCA. This is the first methodological approach to combine PLS-SEM and fsQCA to analyse the adoption intentions of WTs. Although PLS-SEM is able to verify the predetermined relationships between antecedent factors, it cannot explain the details of the relationships. FsQCA provides additional and in-depth explanations for the effective combinations that significantly affect the adoption intentions of WTs for construction safety. In other words, fsQCA offers new and richer insights into the complex trade-off effects of PU, PEoU, SNs, Att, PBC, and PPS, which will better promote the use of WTs in the industry.

6.2. Practical Implications

Safety is always the core objective in construction projects. The use of WTs is supposed to be more proactive and common in the industry. The present article has found the right types of WTs and the predictors for their adoption intentions. The results provide positive and motivating solutions, promoting the greater adoption of WTs in improving construction safety. It also helps to enhance or develop other industrial wearable solutions for occupational safety. To be specific, for wearable sensor tags, Att is the key factor for facilitating adoption intention, and managers should also be aware of PU, as a lack of PU will cause low adoption intentions. Meanwhile, managers should not consider these two factors separately, as there are similar effective factor combinations for adoption intention. For instance, when combining with SNs or PEoU $\times$ SN $\times$ PPS or SN $\times$ PBC $\times$ PPS, the configurations can all result in the presence of adoption intention. The managers can choose different configurations according to the managers' or workers' perceptions of wearable sensor tags. For smart safety hats, PU, SNs, Att, and PPS are the most critical factors that need to be considered in increasing the adoption intention. For smart safety vests, Att and SNs should be paid more attention to, and then combining either PEoU or PPS will be more beneficial to the adoption intention of safety vests. For smart safety insoles, Att, SNs, and PBC are the most important in escalating the adoption intention. Managers should also consider PU, at least. For smart safety glasses, although Att, SNs, and PBC are the most crucial factors in promoting the adoption intention, the combination of PU, PEoU, SNs, Att, and PBC will be the most efficient. For smart wearable wristbands, PPS and PU are the core conditions in facilitating the adoption intention; the combination of PU, PEoU, SNs, Att, and PBC can maximally produce such an intention. Alternatively, the combination of PU, PEoU, SNs, Att, and PPS has the same effect.

6.3. Limitations

Certain limitations need to be considered in this research. First, due to the novelty of WTs in the construction industry, a small sample size and a restricted number of market-ready WTs were employed in this study. Consequently, caution is warranted when generalizing these results to larger populations, and further investigation is necessary to account for potential new WTs and changes in users' behaviour, particularly as adoption maturity reaches certain levels. Future studies should consider a longitudinal action research study action on a particular WT or enrich the samples to verify and reinforce the findings. Second, the data were collected from a single country; thus, a replication study for other languages and cultures should also be conducted to generalize the findings of this research. Third, to have a full picture of the antecedents of the adoption intentions of WTs, the perspectives of managers and workers should be separated to verify whether there exist differences among their viewpoints. Last but not least, the proposed model did not take into account other indirect factors or potential antecedents for adoption intentions (e.g., perceived vulnerability, training, government support); future studies should examine more potential influencing factors to enhance the model's predictability.

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Appendix A. Measurement Items

Construct	Measurement Items	Sources
PPS	It would be safe for me to have [WT Context] disclose my work location. I am comfortable with [WT Context] letting management know about my location. I am comfortable with [WT Context] letting co-workers know about my location.	[58]
PU	Using [WT Context] in my job will help improve my safety. I think [WT Context] will be helpful for my job. Using [WT Context] would enable me to work safely.	[13]
PEoU	[WT Context] would be easy to carry. Wearing [WT Context] would not interfere with my work. I expect to feel comfortable doing my work when wearing [WT Context].	[13]

Construct	Measurement Items	Sources
SN	People who are important to me would think that I should use [WT Context]. People who influence my behaviour would think that I should use [WT Context]. My co-workers would think using [WT Context] is a good idea.	[13]
Att	Using [WT Context] would be a wise decision. I feel positive about using [WT Context]. Using [WT Context] to monitor my safety and health would be beneficial for me.	[17]
PBC	I do not have any resistance to using [WT Context]. I have the technical capability to use and operate [WT Context]. I understand the benefit of using [WT Context].	[17]
AI	I intend to use [WT Context] when I am on the jobsite. I plan to use [WT Context] in the future. All things considered, I will use [WT Context] as long as I have access to them.	[13]

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