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Critical Factors Affecting Intention of Use of Augmented Hearing Protection Technology in Construction

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Abstract: Despite the risk of occupational hearing loss, many noise-exposed construction workers are unwilling to wear hearing protection devices (HPDs) due to their concern about the degraded audibility of environmental sounds. Augmented hearing protection technology that uses advanced artificial intelligenc–based signal processing to amplify safety-critical sounds offers great potential to address the issue. To facilitate the acceptance of this new technology, it is critical to understand the user's intention of use of augmented HPDs. The current state-of-the-art, however, offers little understanding about the user's intention of use of such new technology. This paper fills the gap by exploring factors that determine the user's intention of use of augmented HPDs in the construction environment. Data were collected using questionnaires from 298 practitioners in the US, China, and Japan. The structural equation modeling (SEM) method was adopted for analyzing the collected data. The results denote that the intention of use of augmented hearing protection technology is determined by the user's perceived usefulness of which the perceived ease of use, hearing health, and safety consciousness, trust on autonomy are among the most critical factors. The findings of this study enrich understandings of the theories of technology adoption in construction. It presents a further step towards critical design and implementation considerations for the success of augmented hearing protection technology in the future. **DOI: 10.1061/(ASCE)CO.1943-7862.0002116.** *© 2021 American Society of Civil Engineers.*

Author keywords: Construction safety monitoring; Artificial intelligence; Hearing protection; Technology acceptance model; Structural equation modeling (SEM).

Introduction

As repeatedly reported by many previous studies, despite the risk of occupational hearing loss, many noise-exposed construction workers are unwilling to wear hearing protection devices (HPDs) due to their concern about the degraded audibility of environmental sounds (CPWR n.d.; NIOSH 2019; Seixas and Neitzel 2004). Saleem et al. (2018) reported that 60% of surveyed participants are aware of the importance of HPDs, but only 38% actually use them. This compromise could have substantial adverse social and economic effects upon individuals, business organizations, and society as a whole (Deshaies et al. 2015; Girard et al. 2015). This in turn leads to large economic costs for diagnosis, treatment, rehabilitation, and compensation of hearing-impaired workers. In 2006, the US Veterans Administration reported compensation costs for service-connected hearing loss and tinnitus exceeding \$1.2 billion; an additional \$288 million was spent annually on hearing aids and audiological services for affected veterans (NIOSH 2019).

The use of standard passive HPDs (i.e., earmuffs or earplugs), on the other hand, significantly impacts auditory situational awareness (ASA) (Casali 2010). Many studies found a strong association between inadequate awareness of auditory signals and an increase in unsafe behaviors and subsequent workplace fatalities because of failures to remain alert to hazards (Deshaies et al. 2015; Fang et al. 2016; Girard et al. 2015; Morata et al. 2005). To encourage workers to use hearing protection without compromising their safety, augmented HPDs have been developed in recent years. The technology includes a powered analog or a digital signal filter that blocks unwanted ambient sounds while amplifying important signals such as speeches or warning signals at speakers mounted inside the earcups (Casali 2010). Current products such as Honeywell QuietPro (Charlotte, North Carolina) and Invisio T7 (Chicago) uses mostly analog sound filters. Despite the fact that these analog-based based augmented HPDs help to improve audibility and speech intelligibility, they become ineffective when ambient sounds are complex which deviate significantly from the predefined frequency bands.

Artificial intelligence (AI) has been recently employed to improve the user's ASA. Compared with analog signal processing, the use of deep learning for sound recognition offers a more robust and reliable approach due to its superior advantages of learning temporal information of diverse types of ambient signals. Smart hearing aids which use machine learning to enable near real-time audio classification of conversation and warning signals have been developed to benefit those who suffer from impairment of hearing (Young et al. 2020). In construction, several AI models have been developed capable of recognizing hazards using auditory events of construction equipment operation (Cheng et al. 2017; Lee et al. 2020a). These auditory event detection algorithms offer a fundamental platform that can be integrated into hearing protectors to augment construction workers in detecting safety-critical sounds. Unfortunately, augmented HPDs (either with analog or AI-based signal processing) have not yet been developed or tested for real implementation in construction. The authors of this paper are pioneers

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in developing and testing an AI-based augmented HPD for construction workers (Huang and Le 2020). Still, future development of AI-based augmented hearing protection technology capable of amplifying safety-critical sounds while correctly attenuating noise is a critical need in order to promote the use of hearing protection without scarifying ASA of construction workers.

Understanding the user's needs and concerns is crucial for the development of such technology as the success of introducing any new technology indeed depends on the user's acceptance (Park et al. 2012). This is even more important for the construction workforce, which is considered greatly resistant to innovation and often lagging behind other industry sectors. A recent study found that only 9.6% of construction practitioners use wearable devices (Zack 2016). Given the novelty of augmented HPDs, there is little to no studies has provided any guidance on users' perspective on the technology and their intention of use, especially when advanced AI-based signal processing is deployed. The current hearing augmentation technologies consider neither the human factors nor the complexity that characterize real-world work settings (Clasing and Casali 2014). Previous studies on user acceptance models uncovered critical factors for instance social, organizational, and deployment cost to the adoption of safety devices in construction (Choi et al. 2017; Nnaji et al. 2019; Nnaji and Karakhan 2020). These studies, however, surveyed participants about safety devices in general rather than specific to augmented hearing protectors. They considered neither AI-related issues nor unique characteristics of hearable devices such as the user's perceived health (i.e., hearing loss), perceived audibility to safety events, and their dealing with competing priorities of hearing loss and safety concerns. Thus, the results from previous surveys are less applicable to explaining the intention of use of augmented HPD. There is a great need to improve our understanding of important factors influencing the user's intention of use of augmented HPDs that will not only provide useful information to convince practitioners of its viability but also provide designers with necessary design considerations.

The fill the preceding need, this study aims to identify factors that determine the user's intention of use of augmented HPDs in the construction environment. The aim of this study is based upon related studies on technology adoption, AI devices, audiology, health and safety, and construction safety. This study extends the previous technology acceptance theories for AI-based augmented hearing protection technology as the first study that explores an extensive list of variables ranging from individual, social, organizational, AI, safety, and health. The findings of this study will improve hour understanding of the determinants of intention of use of augmented hearing protectors in construction. This information would help direct the design of the technology that is more acceptable to the user. The study is expected to facilitate the acceptance of augmented hearing protection technology, promote the use of hearing protection, reduce hearing loss, and enhance safety.

Literature Review

Augmented Hearing Protection Devices

In order to augment the audibility of safety-critical sounds in noisy workplaces such as construction sites, researchers have developed various signal processing algorithms for hearing protectors. The current state of the art on augmented HPDs mainly relies on powered analog sound filters. For example, Bernstein et al (2014) developed a bandpass filtering algorithm integrated into an earmuff to remove unnecessary frequency bands beyond the range of warning signals such as back alarms. With this system, environment sounds are received by an external microphone mounted on the surface of the ear cup before being filtered and reproduced at small internal speakers mounted inside the earcup. The study showed that their algorithm can enable the detection of alarms at signal-to-noise ratios as low as −30 dB and improve the audibility by 7 dB compared with a passive HPDs. Using the same principle, they designed and tested another sound filter specifically for augmenting the hearing communication buried in loud background noise to improve speech intelligibility (Bernstein et al. 2013). A few examples of commercialized HPDs adopting such analog sound filtering methods are QuietPro and Invisio Elvex Impulse Com-655TM, the Bilsom/Howard Leight Impact by Sperian, Peltor Tactical, and the Jackson Safety Falcon (Casali 2010; Gaston et al. 2018). The number of commercialized products is too exhaustive to be included here. Tactical communications and protection systems (TCAPS) are another common type of augmented HPD technologies specially designed to improve face-to-face communication in noise. TCAPS integrates radio communication headsets with hearing protection to allows protection from the ambient noise, but also facilitates the understanding of radioed speech at lower at-ear presentation levels (Casali 2010). Active noise reduction (ANR), a technique that generates adverse sound wave to cancel the incoming undesired noise, is also commonly integrated into TCAPS to provide further noise cancelation. The 3M Peltor PowerCom Plus, 3M PELTOR WS 100 Headsets, and Nacre QuietPro are among the best examples of TCAPS with ANR (Giguère et al. 2011, 2013; Nakashima and McDavid 2018).

Current analog-based augmented hearing augmentation technologies receive various criticism. First, they fail to consider the complexity that characterizes real-world work settings. The reliance upon predefined frequency band for sound filtering and attenuation falsely prevent users from hearing important sounds (Clasing and Casali 2014). Also, various field tests on commercial technologies reported that it is best used only for low-frequency noise (less than 1,000 Hz) that is repetitive, continuous, and does not change significantly in its spectrum or level (Casali et al. 2004). More recent work also revealed the negative impact of traditional HPDs on the auditory performance of workers. For example, Mlynski and Kozlowski (2019) reported that some models of level-dependent HPDs made a noticeable reduction in the user's ability to localize back-up alarms. Experiments by Smalt et al. (2020) demonstrated that active HPDs increased hearing efforts (e.g., measured by reaction time and working memory) among the participants. It is found that there are possibly several ergonomics and interface issues with augmented HPDs. For example, the surveyed soldiers who used TCAPS devices on battlefields complained that their own body-generated sounds (e.g., whispering or foot walk on leaves) become too loud when switching the device to high gain settings, making them worry if their own movements are not sufficiently stealthy (Casali 2010). Nonetheless, because current active HPDs are developed based on signal processing, they require substantial effort and sufficient auditory sensory adaptation of users before being put into use in real situations when sounds are unpredicted (Casali and Robinette 2015). Therefore, more laboratory testing and research are required in order to address the shortcomings of the technology.

Recently, AI has been increasingly implemented to improve the user's auditory situational awareness. Unlike the static frequency-based auditory filtering techniques deployed in traditional HPDs, AI models offer a more robust means that can accurately distinguish various types of unimportant and import sounds and detect their location by learning from a large amount of sequential acoustical data. As a result, the use of AI-based signal processing in HPDs will help to avoid the amplification of such unwanted sounds that are unnecessary for the worker's safety and work, thus reducing auditory cognitive demand. Due to this superior capability, machine learning models have been increasingly deployed on smart hearing aids to enable near real-time audio classification of conversation and warning signals for hearing impairment users (Young et al. 2020). Other researchers employ advanced deep learning architectures to help the listener quickly detect auditory safety cues in different contexts, such as indoor and public environments, medical, and health care systems (Clavel et al. 2005; Cramer et al. 2019; Salamon et al. 2014; Salamon and Bello 2017; Vacher et al. 2004). To the best of our knowledge, AI has yet to be deployed on hearing protectors to improve occupational safety despite recent progress made on audio signal processing in construction. Research on ASA in construction has been mainly concerned with the automated assessment of hazards associated with the activities of construction heavy equipment based on different sound patterns generated by such equipment. For instance, Cheng et al. (2017) developed an audio-based model capable of accurately identifying various actions of construction heavy equipment. Lee et al. (2020a) trained a larger dataset of 64,700 instances of construction equipment sound signals using Random Forest and achieved an impressive accuracy of 93.16%. The model's accuracy was reduced to 85% when being tested with real-world construction sites where the audio signals of interest are often mixed with other background noise. To improve the robustness of hazard assessment necessary for audio-based monitoring of construction safety, Lee et al. (2020b) developed a risk-based signal processing method that analyzes the historical occupational injury and illness data to evaluate the hazardousness of audio events detected by a machine learning model. The framework includes the integration of a daily project schedule to generate timely alerts to construction workers regarding safety hazards at a work zone and time. Although the proposed system provides impressive sound classification results, it is applicable to the recognition of a few types of heavy equipment only rather than to a broad range of safety cues such as waring alarms or equipment malfunction. Despite the limitation, the encouraging results of recent studies have paved the foundation for future deployment of AI-based sound filtering on hearing protectors. This innovative technology would help improve safety by augmenting the hearing of critical sounds with less cognitive demand by effectively suppressing undesired noises. It could also promote the use of hearing protection among noise-exposed workers, thus reducing the hearing loss and associated social and economic consequences for millions of noise-exposed workers across many industries.

Prior Knowledge on Technology Acceptance in Construction

Earlier efforts in technology adoption in construction was mostly centered on information technologies. Peansupap and Walker (2005) identified 11 factors that influence information and communication technology (ICT) diffusion and adoption by organizations in Australia. The factors were grouped into management, individual, technology, and workplace environment categories. Similarly, Ahuja et al. (2009) found technical, managerial, and people issues as primary factors that affect ICT adoption in construction. Another empirical study by Son et al. (2015) revealed that top management support, subjective norm, compatibility, and computer self-efficacy are critical factors affecting architects' behavioral intentions to adopt building information modeling (BIM). They also found the effect of the factors on behavioral intentions are mediated by perceived usefulness and ease of use. Specifically for web-based training (WBT) in the construction industry, it was found that user satisfaction is a key indicator of acceptance of the technology, which is mainly driven by the user's belief about usefulness and ease of use rather than enjoyment, social influence, and information quality (Park et al. 2012).

More recently, a few studies focusing on investigating theories explaining the industry's adoption of safety technologies have been carried out. Choi et al. (2017) investigated workers' perception toward wearable devices for occupational safety and health (i.e., smart vest and GPS for location tracking, wristband-type activity trackers, physical sensors). The study indicated that perceived usefulness, social influence, and perceived privacy risk are associated with workers' intention to adopt both smart vest and wristband. The study also found that workers' experiences with wearable devices positively moderates the association between perceived usefulness and adoption of smart vest. Regarding work context, foremen are more likely to be influenced by perceived usefulness than workers with regard to using a wristband (Choi et al. 2017). Another study on the acceptance of safety technologies by Nnaji et al. (2019) found 12 individual and technical predictors and a few external and organizational predictors. They also found that smaller-sized companies and workers with less experience tended to rate a significantly lower importance level on the predictors in the individual and technology categories. Nnaji and Karakhan (2020) further identified the influence of investment cost and training as the primary challenges to the use of technologies for managing occupational safety and health in construction projects.

Despite the significant effort that has been made, previous studies focused either on factors affecting the technology adoption of a broad range of safety technologies as well as other general technologies in construction rather than specific to augmented HPDs. Prior studies discussed previously lack consideration of factors specific to hearing health and noise exposure context. Additional, as suggested by Casali (2010), more research efforts including surveying future users and field tests are needed to facilitate successful adoption of intelligent HPDs, particularly regarding ergonomics, demographic backgrounds, interface issues, and user's auditory sensory factors. Moreover, the novelty of AI deployment for general technologies in construction and on HPDs requires further studies to expand the current acceptance theories for AI-based hearables. Considering AI factors is critical because the level of familiarity with AI may significantly influence the acceptance of a technology with AI (Young et al. 2009). Therefore, understanding factors that control the success of implementing augmented HPDs will provide constructive directions in improving its adoption rate. The current research seeks to close this gap by proposing a comprehensive model that includes the main drivers of user adoption of AI-based augmented HPD. The next section presents the study's specific objectives.

Research Goal and Objectives

As shown in the previous section, despite various technology acceptance models have proposed, no model exists that allows us to understand the intention of uses of advanced augmented HPDs, especially when AI is deployed due to the novelty of AI-based augmented hearable devices. The study aims at extending the knowledge on technology adoption in construction by developing a novel model of factors determining the intention of use of augmented HPDs among construction workers. To achieve the research goal presented previously, the study includes the following three primary objectives:

1. identify potential variables determining the intention of use through an extensive review of related studies;
2. collect quantitative data from construction practitioners; and

J. Constr. Eng. Manage., 2021, 147(8): 04021088

3. conduct statistical analysis to identify critical factors influencing the user's intention of use.

Research Methodology

To achieve the objectives of the study, a mixed method, which is commonly used for technology adoption by many researchers (Belanche et al. 2019; Nnaji and Karakhan 2020), was implemented. The approach relies on a systematic literature review, expert interviews, a survey of industry professionals, and statistical analysis. Fig. 1 depicts the research structure utilized in the present study. Specifically, to achieve the first objective, a literature review was conducted following content analysis to identify potential factors. The potential impact of the identified factors on intention of use was hypothesized to formulate the research hypotheses. The second objective was performed through a survey to obtain the user's background information, quantitative data associated with the factors for each participant, along with their intention of use of the technology. The third objective was achieved by conducting various statistical analyses using a well-established statistical method called SEM to test the hypotheses. The testing result was used to identify significant factors. The following sections explain the methodology in detail.

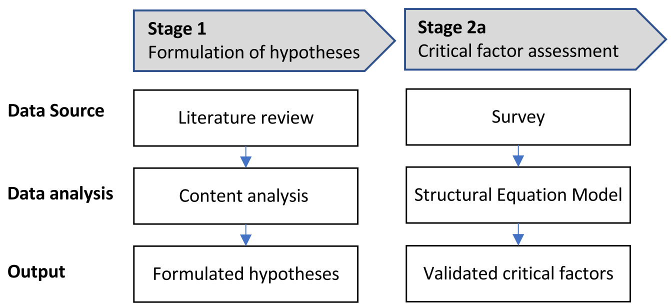

Fig. 1. Overview of research methodology.

Literature Search to Identify Factors and Formulate Research Hypotheses

The factors and hypotheses of the present study were built on an extensive review of: (1) fundamental technology adoption theories including technology acceptance model (TAM) (Davis 1993) and the theory of planned behavior (TPB) (Schifter and Ajzen 1985); and (2) related studies on hearing protection, safety technologies, and other technologies that deploy AI. Relevant articles were identified using two primary databases—Web of Science and Scopus—using keywords pertinent to the study (e.g., technology adoption, safety technology, AI adoption). The review includes existing literature on technology adoption in construction and other industry sectors to identify factors that can influence the adoption of technology in the construction industry. Papers that are beyond the preceding stop were discarded. Relevant papers were carefully reviewed, a thematic coding process was implemented to delineate the identified predictors into categories.

The result of the review process yielded 11 factors that may have direct and indirect influence on the intention of use of augmented HPDs through 17 interdependence hypotheses. Based on this finding, a hypothesized model explaining the intention of use of augmented HPDs was proposed as shown in Fig. 2. As shown in the figure, the model includes: (1) potential factors categorized into enablers and inhibitors of the construction practitioner's intention to use augmented HPDs, and (2) hypotheses on the potential interactions of these determinants on the construction practitioner's

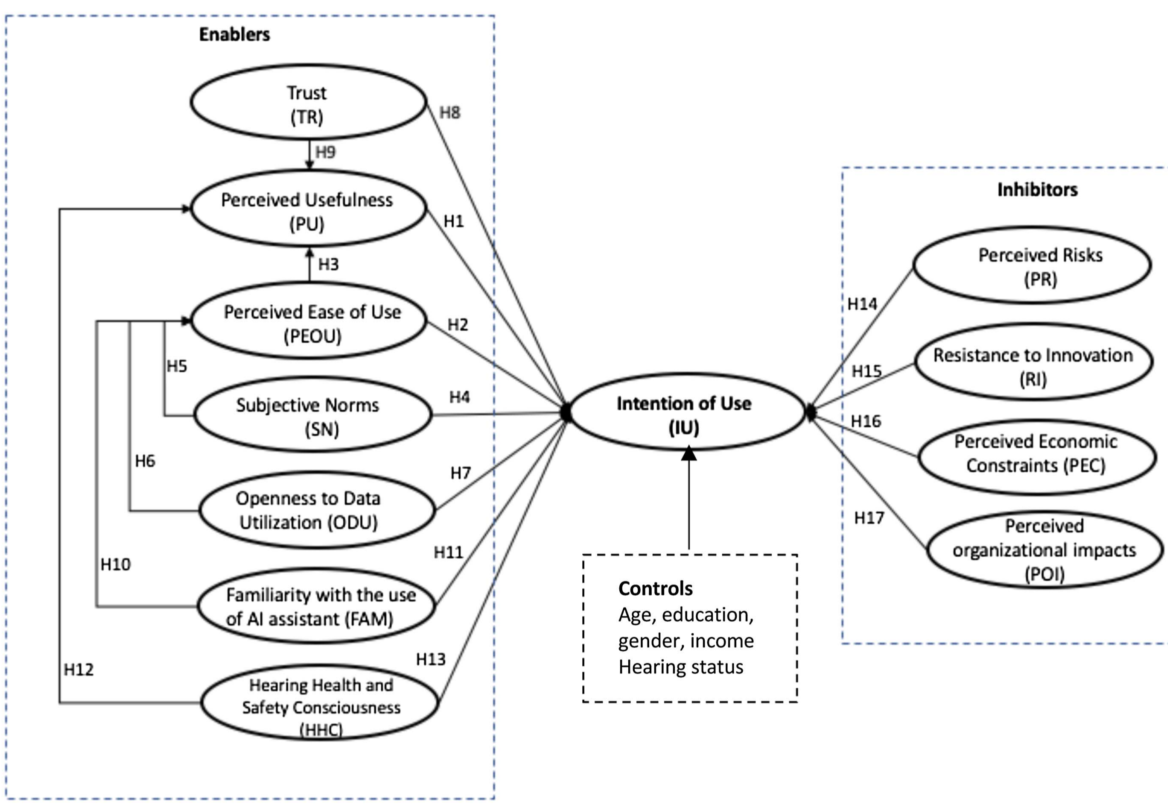

Fig. 2. Hypothesized model for augmented HPDs acceptance.

intention to use augmented HPDs. In addition, adopting what suggested by previous theories on wearable technology adoption (Choi et al. 2017), all of the hypotheses in the present study take into account the effects of the following demographic controls: age, education, gender, income, and hearing status. Theoretically, if a certain hypothesis is tested significant when controlling a demographic variable (e.g., gender), it is true regardless of an individual's demographics (Kock 2011). To be clear, the scope of this study does not involve the assessment of the moderator effects of the demographic variables on the strength of the relations between an independent and a dependent variable. The details of the research hypotheses along with their relevant theories are presented in the following subsections.

Hypotheses Related to TAM

TAM, proposed by Davis (1993), has perceived as the most influential theory in the field of user behavior of information system. The TAM theory explains technology adoption through the following routes: (1) external variables decide the perceived usefulness (PU) and perceived ease of use (PEOU), (2) PU and PEOU impact the attitude towards using, (3) attitude towards using influences the behavioral intention to use (IU), and (4) behavioral intention to use decides actual usage behavior. In addition, the theory indicates that PEOU has positive impact on PU, and PU also influences IU positively. Recently studies on wearable devices in construction found that the mediation effect of attitude towards using was weakly associated with the effect both PU and PEOU had on IU, and thus attitude was removed from TAMs (Ye et al. 2019). By adopting TAM with consideration of the findings for construction safety technology, it is reasonably inferred that PU and PEOU contribute positively to the construction practitioners' intention to use augmented HPDs, and PEOU contributes positively to the construction practitioners' PU of augmented HPDs. Therefore, Hypotheses H1, H2, and H3 were proposed as follows:

H1. PU has a positive impact on the construction practitioner's intention to use augmented HPDs.

H2. PEOU has a positive impact on the construction practitioner's intention to use augmented HPDs.

H3. PEOU has a positive impact on the construction practitioner's PU of augmented HPDs.

Hypotheses Related to the Theory of Planned Behavior (TPB)

The TPB theory explains that human and social variables including subjective norm (SN), i.e., the perception of whether others think they should engage in using, could influence the adoption of an innovation (Mun et al. 2006). The idea was to account for cognitive and situational resources that predict and explain health behaviors and intentions. The TPB framework is found to be well supported by empirical evidence in multiple studies (Ajzen 1991; Lee et al. 2011; Zhang and Ng 2013). Based on TPB, it is reasonably inferred that subjective norm contributes positively to construction practitioner's perceived ease of use of augmented HPDs, and construction practitioner's intention to use augmented HPDs. Therefore, Hypotheses H4 and H5 were proposed as follows:

H4. SN has a positive impact on the construction practitioner's IU augmented HPDs.

H5. SN has a positive impact on the construction practitioner's PEOU of augmented HPDs.

Hypotheses Related to Wearable Technologies

With respective to the use of wearable technologies, previous studies have reported data security and encryptions as the most concerning issues in facilitating their adoption (Kurkovsky et al. 2007; Pantelopoulos and Bourbakis 2009). With augmented HPDs, users are expected to wear an earmuff or earplug which is equipped with advanced signal processing algorithms that processes audio signals collected by external microphone mounted outside the earmuff. Due to the high requirement of computation resource, cloud-based signal processing may be required to make real-time sound detection. To this regard, field workers may not be willing to share their working status with their supervisors. This is supported by Choi et al. (2017)'s study which found that the privacy concern into perceived privacy risk, which in turn is negatively related to intention to use. In light of the this, hypotheses H6, H7, H8, and H9 were reasonably proposed as follows:

H6. Openness towards data utilization (ODU) has a positive impact on the construction PEOU of augmented HPDs.

H7. ODU has a positive impact on the construction practitioner's IU augmented HPDs.

H8. Trust (TR) has a positive impact on the construction practitioner's IU augmented HPDs.

H9. TR has a positive impact on the construction practitioner's PU.

Hypotheses Related to AI

AI has played a role in assisting human workers in their daily activities, but it also triggers many worries because users are required to adapt the new human-AI interaction model. It is found that users with higher level of familiarity with AI innovation will see more values from the technology in terms of usefulness, because they have more knowledge and practice of these systems, which build up a sturdy personal predisposition about accepting the innovation (Belanche et al. 2019). Because field workers diverge in the level of familiarity with the use of AI assistants (FAM) (Young et al. 2009), it is reasonably inferred that FAM contribute positively to PEOU and IU of augmented HPDs. Accordingly, Hypotheses H10 and H11 were proposed as follows:

H10. FAM has a positive impact on the construction practitioner's PEOU of augmented HPDs.

H11. FAM has a positive impact on the construction practitioner's IU augmented HPDs.

Hypotheses Related to Perceived Hearing Health and Safety Awareness

Researchers in the field of health information technology found that the motivation to use innovative technologies is mainly driven by perceived health condition, their concerns about their wellness, and PU (Ahadzadeh et al. 2015). For field construction workers who often suffer from hazardous noises at construction sites, their hearing health concerns may have a direct effect on augmented HPD adoption. Meanwhile, because earplugs prevent users from receiving environment auditory signals, field workers would miss the useful audio cues such as alerts. Under such circumstance, field workers' perceptions on safety level of HPDs would influence perceived usefulness and behavioral intention to use augmented HPDs. Therefore, it is reasonably inferred that hearing health and safety consciousness contribute positively to the construction practitioner's perceived usefulness of augmented HPDs, and their intention to use augmented HPDs. Therefore, the following hypotheses were proposed:

H12. Hearing health and safety consciousness (HHC) has a positive impact on the construction practitioner's PU of augmented HPDs.

H13. HHC has a positive impact on the construction practitioner's IU augmented HPDs.

Hypotheses Related to Inhabitation

Previous studies on the adoption of information systems (IS) have also determined by inhibiting factors such as perceived risk (PR), resistance to innovation (RI), perceived economic constraint (PEC), and perceived organizational impact (POI) (Dou et al. 2017; Hsieh 2015). PR is a latent factor that presents the uncertainty and seriousness of one individual when using a new technology with respect to performance, safety, psychological, or social risks (Egea and González 2011; Im et al. 2008). RI refers to users' attempts to hold the norms related to past experiences that restrict the adoption of new technology (Bhattacherjee and Hikmet 2007; Dou et al. 2017). PEC refers to perceptions of the economic constraints. POI is regarded as perception of the organizational and societal constraints or impediments. In the construction context, Nnaji et al. (2019) revealed that the regulations, policies, and procedures of approving safety-related execution usually influence the possibility of adopting new technology in the organization. Accordingly, it is reasonably inferred that these inhibiting factors contribute negatively to the construction practitioner's IU augmented HPDs in this study. Therefore, Hypotheses H14, H15, H16, and H17 were proposed as follows:

H14. PR has a negative impact on the construction practitioner's IU augmented HPDs.

H15. RI has a negative impact on the construction practitioner's IU augmented HPDs.

H16. PEC has a negative impact on the construction practitioner's IU augmented HPDs.

H17. POI has a negative influence on the construction practitioner's IU augmented HPDs.

Hypotheses Testing Using Survey Data from Industry Professionals

In order to test the hypothesis, this research aims to investigate the relationships between variables in the proposed model by validating associated hypotheses. A survey design and analysis were adopted as the quantitative approach of the study.

Survey Design and Validation

The main survey was conducted in the form of a questionnaire targeting both field practitioners and industry professionals, which consists of three primary sections as shown in the Appendix. The first section introduced fundamental know-how of augmented HPDs such as working principles, working modes. After reading the product introduction, participants were expected to answer a few questions that help to filter out unqualified responses. Specifically, the questionnaire includes questions to test if the respondent has read and understood the content explaining augmented HPDs. The second section seeks demographic information from the participants. In the third section, the participants were asked to rate the perceived importance level for each factor using a five-point Likert scale where 1 represents totally disagree and 5 represents totally agree. In addition, the participants were asked to indicate their IU using the same scale. Note that all of the factors are latent variables that may be difficult to be measured directly. The quantification of each variable is measured indirectly through a number of specific questions addressing its different aspects (see the Appendix for the full questionnaire). Moreover, several multiple choice-trap questions (it is very unlikely to select a wrong answer if one reads the question carefully) were included in the questionnaire for the purpose of data validation. The inclusion of these questions would be helpful to detect unreliable responses.

Before conducting the survey, content validation and reliability of the data collection instrument were carried out using an expert panel review in the form of sending them a preliminary questionnaire (Bernard and Bernard 2013). Experts were selected from databases such as Google Scholar, ResearchGate, and LinkedIn by their academic or occupational relevance to the topic and academic influence. Five experts including three researchers and two professionals in practice were invited to review the questionnaire. Three associate professors with the keyword tag Construction Management at Google Scholar respectively from the US, Japan, and China, and two US-based civil engineers with approximately 20 years of working experience, were engaged to review the questionnaire, specifically: (1) identifying whether each item would be able to reflect the variable it served, (2) examining whether the descriptive language of the survey would be accurate and appropriate to capture the targeted data, and (3) estimating the time of answering a completed questionnaire (Feng and Trinh 2019). There were several revisions and amendments on the survey after receiving their feedbacks. For example, the question "the inventory management cost of augmented HPDs would be large" was added to the list of elements of perceived economic constraints. Subjective norms were further explained by three items compared to the previous version of one item. Furthermore, the language usage in the survey was polished.

Data Collection

The questionnaire survey was then designed on the Qualtrics platform and elicited responses from the participants about the importance of the identified factors and their IU. The targeted participants were hereby defined as construction workers and engineers who are currently working or ever had construction experiences. The data collection procedure involved two steps. Firs, an invitation was sent out through the crowdsourcing website Amazon Mechanical Turk (Mturk), WeChat Official Accounts Platform, LinkedIn, and limited visits to construction sites. Of those, Mturk workers received monetary compensation for participating in the study while those from other sources were recruited on a fully voluntary basis without receiving any compensation. The choice of using paid MTurk workers as a supplement was supported by the literature, which demonstrated that realistic compensation rates do not affect data quality, and this approach is at least as reliable as traditional methods (Buhrmester et al. 2016). Once the potential participants agreed to participate in the research, they would have access to the online survey through the given link. Step two involves providing their consent to participate in the research and answering the online questionnaire carried out by the respondents with the aid of Qualtrics survey software.

It was anticipated that there are some potential threats to reliable research data in this study as a result of the limitations of an online survey method. In this study, the impact of this limitation was minimized by the following measures: (1) ensuring the voluntary nature of participation in the questionnaire, anonymity of respondents, and confidentiality of respondents' responses in order to prevent lies and deceptions; (2) assuring the comprehensiveness and clarity of the research instrument in terms of instruction, statements, and questions in order to avoid unintended error made by respondents when answering the questionnaire; (3) respondents were encouraged to review and revise their recorded responses; and (4) a careful check on the completed questionnaire and data problems (e.g., survey completion time, consistency checks, incorrect answers to trap questions) carried out by the researcher. There were 298 valid responses collected. An additional 68 participants began the survey but failed to complete it either quitting halfway or being filtered out by trap questions and other quality control measures previously, resulting in a dropout rate of 18.5% (68/366).

Statistical Methods—Structural Equation Modeling

To test the hypotheses associated with the paths of the proposed model, this study adopted the SEM method, which is a popular statistical means for characterizing relationships among observed variables and latent variables by multiple interconnect linear equations (Feng et al. 2017). SEM is considered as a more powerful method than regression because it can capture the complex relationships between variables where a dependent variable in one model equation can become an independent variable in other equations (Gunzler et al. 2013). SEM algorithms can be categorized into: (1) partial least squares (PLS) algorithms, (2) covariance-based analysis algorithms (CB), and (3) simultaneous equations regression algorithms. PLS-SEM was applied in the present paper due to the average sample size and online questionnaire distribution style according to suggestions made by the literature (Falk and Miller 1992; Fornell and Bookstein 1982). In this research, 17 hypotheses that described relationships among 12 factors in the model were tested (Fig. 2). As mentioned earlier, all of the hypotheses were tested taking into account the effects of the following controls: age, education, gender, income, and hearing status. By controlling these demographic factors, the sign and significance of the testing results will not change regardless of the participants' demographic characteristics (Kock 2011).

SEM includes measurement model and structural model analyses. The purpose of measurement model analysis is to test the reliability and validity of the construct measures, so as to interpret the applicability of their inclusion in the path model. In statistics, a construct refers to a concept (i.e., perceive ease of use) that is not directly observable. It is necessary to use multiple measurement items to quantify a construct. The 12 factors investigated in this study were treated as constructs and their values are measured through various measurement indicators (see the Appendix). The measurements are typically considered reliable if their loadings are above 0.40. Besides, Cronbach's alpha and composite reliability can be used to evaluate the internal consistency reliability of measured constructs (the score should be over 0.70). The loadings for all items of each measurement model and average variance extracted (AVE) evaluate the convergent validity of measured constructs (AVE should be higher than 0.5). In addition, the discriminant validity of the measured constructs was evaluated using the following criteria: (1) an indicator's outer loadings on a contruct should be higher than all its cross loadings with other constructs (cross-loading); and (2) the square root of the AVE of each construct has to be larger than its highest correlation with any other construct (Fornell-Lacker criterion) (Hair et al. 2013).

The relationships between constructs within a specific model are covered in structural model analysis. SEM distinguishes variables in the model into: (1) endogenous variables—those with at least one incoming link and their values are affected by other variables in the model; and (2) exogeneous variables—those without any incoming link and their values are determined outside the model. In our hypothesized model (Fig. 2), IU, PEOU, and PU are endogenous factors. Exogenous factors include PR, RI, PEC, POI, HHC, FAM, ODU, SN, TR, and demographic controls. Of those endogenous factors, IU serves as the dependent variable in every relationship with other variables while PEOU and PU serve as both dependent and independent variable. For demographic controls, they were modeled as independent variables with a direct link to IU.

The PLS-SEM algorithm estimates the path coefficients and their statistically significant level subject to maximizing the explained variance of the predicted constructs, which also means minimizing the unexplained variance (Bentler and Huang 2014; Hair et al. 2013; Lohmöller 2013). In general, a bootstrapping technique can be applied to test the significance of coefficients in PLS-SEM (Davison and Hinkley 1997; Efron and Tibshirani 1986). In this research, bootstrapping was utilized to validate the significance of coefficients (factor loadings and path coefficients) explored in the PLS-SEM models through SmartPLS (version 3.2.7). As suggested by Hair et al. (2016), the number of bootstrap samples was set to 5,000.

Survey Results and Data Analysis

Demographic Information of Survey Participants

As mentioned earlier, a survey was sent out to industry professionals asking them to quantify each of the measurement items of the factors. After a period of two months, a total of 298 valid responses was received. The results indicate that responses were from various states in the US along with others from China and Japan. Participants ranged from 18 to 69 years old, with median age of 30. The majority (79.2%) was identified as male while 20.8% was female. Additionally, 79.5% of the participants hold a bachelor or higher degree. Participants' occupations diverged from site engineer to carpenter. 61% of them were workers and 39% of them were engineers. In terms of self-reported level of hearing loss that participants perceived they were suffering, all participants reported they have at least slight level hearing loss. 73.2% of the participants reported that they were exposed to noises of different levels during working.

Measurement Model Analysis

Before the structural model analysis is performed, the satisfactory reliability and validity of the measurement model need to be examined (Fornell and Larcker 1981). Table 1 illustrates the results of measurement model evaluation, including: (1) factor loadings and t-value of individual measurement items, (2) Cronbach's Alpha, (3) composite reliability, and (4) average variance extracted values for respective dimensions within their corresponding constructs. Notably, the values of the calculated Cronbach's alpha reliability and composite reliability are over 0.7, which implies that internal consistency reliability of the related constructs was satisfactory.

The loadings for all items are above 0.4 in each measurement model. Additionally, the t-value of all individual measurement items is higher than 2.57. This fact indicates that the association between measurement items and their corresponding constructs are significant. Also, AVE scores are higher than 0.5, meaning that each construct explained at least 50% of each measurement items' variance. Furthermore, it can be interpreted that convergent validity of the measured constructs was satisfactory.

The cross-loading analysis results of discriminant validity test (Fornell-Lacker analysis) are presented in Table 2. It reveals that all indicators loaded greater on the construct that they were measured, in comparison to other constructs in the models. These results validated the required discrimination of the constructs. Moreover, by comparing the square root of AVE scores and correlation coefficients between constructs, the discriminant validity of constructs was further verified (Table 3). As a result, discriminant validity was satisfactory, and the constructs were different from each other.

According to the results of PLS-SEM, the major variables in this study met all the criteria for determining the reliability and validity of each construct. Thus, the measurement models was valid for evaluating structural models. The confirmed constructs and their corresponding measurement indicators can be found in Table 4.

Structural Model Analysis

In evaluating the structural model, the path coefficients between research variables were examined. The results are shown in Fig. 3 and Table 5. In Fig. 3, the solid lines with estimated standardized effect coefficients (β) represent significant paths where the hypotheses were supported. Accordingly, as shown in Fig. 3, there are significant positive correlations between: (1) PU and IU ($\beta = 0.304$, $\rho < 0.01$); (2) familiarity with the use of AI assistance and PEOU

Table 1. Measurement model evaluation

Constructs	Measurement items	Loading	t-value	Cronbach's alpha	Composite reliability	AVE
PEOU	PEOU1	0.781	27.413	0.771	0.845	0.523
	PEOU2	0.691	16.961			
	PEOU3	0.721	17.89			
	PEOU4	0.666	15.905			
	PEOU5	0.75	24.155			
FAM	FAM1	0.833	38.35	0.7	0.816	0.528
	FAM3	0.692	15.552			
	FAM4	0.672	14.963			
	FAM5	0.698	15.046			
HHC	HHC1	0.915	75.489	0.734	0.881	0.788
	HHC3	0.859	33.247			
IU	IU1	0.858	46.171	0.711	0.838	0.634
	IU3	0.781	20.446			
	IU4	0.745	17.534			
ODU	ODU1	0.863	15.968	0.844	0.904	0.76
	ODU2	0.828	12.48			
	ODU3	0.921	31.714			
PEC	PEC1	0.856	22.637	0.705	0.833	0.629
	PEC2	0.644	5.921			
	PEC3	0.86	14.968			
POI	POI1	0.844	29.774	0.732	0.848	0.651
	POI2	0.706	12.897			
	POI3	0.863	39.64			
PR	PR1	0.87	10.58	0.738	0.843	0.643
	PR2	0.762	6.684			
	PR3	0.769	6.229			
PU	PU1	0.718	17.348	0.765	0.841	0.515
	PU2	0.696	15.718			
	PU3	0.726	20.772			
	PU4	0.696	18.473			
	PU7	0.751	21.06			
RI	RI1	0.892	41.402	0.745	0.887	0.797
	RI3	0.893	34.537			
SN	SN1	0.878	45.004	0.788	0.877	0.704
	SN2	0.78	21.971			
	SN3	0.856	34.45			
TR	TR1	0.794	33.518	0.703	0.817	0.528
	TR2	0.768	32.046			
	TR3	0.65	16.721			
	TR4	0.686	17.396			

$(\beta = 0.462, \rho < 0.01)$; (3) openness towards data utilization and PEOU $(\beta = 0.125, \rho < 0.01)$; (4) SN and PEOU $(\beta = 0.341, \rho < 0.01)$; (5) PEOU and PU $(\beta = 0.352, \rho < 0.01)$; (6) hearing health and safety consciousness and PU $(\beta = 0.357, \rho < 0.01)$; and (7) trust and PU $(\beta = 0.249, \rho < 0.01)$. In addition, the squared multiple correlation (R^2) is a measure of the model's predictive power and is estimated as the squared correlation between a specific endogenous construct's actual and predicted values. Relatively high R-square values of IU, PEOU, and PU were obtained in the model. The model explains 53.3% of IU's variance, 48.6% of PEOU's variance, 60.4% of PU's variance. Table 5 summarized the hypotheses, path coefficients obtained from the PLS analysis, t-values, the associated levels of significance for each path and the squared multiple correlations (R^2). Therefore, hypotheses H1, H3, H5, H6, H9, and H10 are supported. The statistical results of these hypotheses and their implications are discussed in the next section.

Discussions

Impact of Perceived Usefulness on Intention to Use

The results of structural model analysis confirmed that there was a great direct positive correlation between perceived usefulness and intention to use augmented HPDs, illustrated by $(\beta = 0.304, \rho < 0.01)$ (Fig. 3 and Table 5). This result indicate that construction practitioners are more likely to use augmented HPDs when they have a better understanding of the usefulness and function of such technology. This finding can be supported by previous studies in the fields of artificial intelligence, hearing protection, construction, where perceived usefulness is proven to significantly influence the intention to use a new technology. A study by Hwang and Lee (2017) explored that usefulness is positively associated with workers' acceptance to adopt a smart vest that can monitor physiological status. Adapa et al. (2018) recognized that perceived

J. Constr. Eng. Manage., 2021, 147(8): 04021088

Table 2. Analysis of cross-loadings

Items	FAM	HHC	IU	ODU	PEC	PEOU	POI	PR	PU	RI	SN	TR
PEOUU1	0.44	0.369	0.504	0.141	0.345	0.781	0.347	0.132	0.568	0.372	0.413	0.508
PEOU2	0.406	0.289	0.377	0.108	0.186	0.691	0.182	0.106	0.432	0.273	0.393	0.357
PEOU3	0.495	0.318	0.437	0.118	0.18	0.721	0.187	0.21	0.44	0.363	0.38	0.318
PEOU4	0.424	0.264	0.387	0.199	0.236	0.666	0.222	0.181	0.414	0.241	0.287	0.275
PEOU5	0.451	0.396	0.454	0.203	0.275	0.75	0.386	0.117	0.471	0.471	0.395	0.435
FAM1	0.833	0.418	0.432	0.14	0.321	0.522	0.207	0.246	0.42	0.403	0.327	0.329
FAM3	0.692	0.27	0.27	0.159	0.263	0.384	0.214	0.312	0.197	0.366	0.158	0.255
FAM4	0.672	0.367	0.377	0.174	0.173	0.452	0.254	0.155	0.398	0.233	0.331	0.404
FAM5	0.698	0.32	0.309	0.019	0.334	0.4	0.227	0.457	0.332	0.238	0.261	0.274
HHC1	0.431	0.915	0.506	0.037	0.235	0.444	0.48	0.225	0.618	0.329	0.537	0.421
HHC3	0.426	0.859	0.389	0.025	0.308	0.357	0.432	0.227	0.494	0.251	0.515	0.406
IU1	0.396	0.462	0.858	0.04	0.278	0.52	0.444	0.07	0.639	0.306	0.51	0.502
IU3	0.383	0.391	0.781	0.031	0.25	0.448	0.397	0.286	0.484	0.188	0.395	0.409
IU4	0.389	0.358	0.745	0.203	0.299	0.463	0.265	0.109	0.442	0.292	0.358	0.4
ODU1	0.152	0.136	0.1	0.863	0.077	0.2	0.101	0.037	0.11	0.233	0.092	0.103
ODU2	0.163	−0.074	0.056	0.828	−0.019	0.14	−0.223	0.012	−0.017	0.184	−0.046	−0.153
ODU3	0.142	−0.002	0.114	0.921	0.035	0.201	−0.085	0.012	0.028	0.228	−0.006	−0.071
PEC1	0.356	0.289	0.338	0.035	0.856	0.296	0.253	0.224	0.329	0.265	0.242	0.385
PEC2	0.209	0.161	0.201	0.028	0.644	0.269	0.192	0.212	0.211	0.057	0.201	0.295
PEC3	0.297	0.24	0.255	0.038	0.86	0.253	0.252	0.276	0.228	0.13	0.165	0.287
POI1	0.231	0.419	0.416	0.008	0.243	0.252	0.844	0.184	0.42	0.229	0.459	0.447
POI2	0.228	0.34	0.292	−0.091	0.233	0.293	0.706	0.234	0.375	0.141	0.333	0.438
POI3	0.289	0.478	0.413	−0.071	0.245	0.361	0.863	0.204	0.458	0.241	0.47	0.511
PR1	0.408	0.212	0.189	0.135	0.266	0.215	0.183	0.87	0.172	0.148	0.166	0.12
PR2	0.239	0.18	0.143	−0.135	0.205	0.133	0.216	0.762	0.136	0.048	0.07	0.143
PR3	0.231	0.242	0.077	0.022	0.244	0.112	0.231	0.769	0.149	0.028	0.127	0.093
PU1	0.199	0.517	0.395	−0.029	0.228	0.351	0.507	0.107	0.718	0.198	0.546	0.456
PU2	0.228	0.457	0.399	0.007	0.206	0.384	0.435	0.099	0.696	0.162	0.484	0.493
PU3	0.234	0.47	0.482	−0.004	0.226	0.396	0.35	0.023	0.726	0.181	0.579	0.419
PU4	0.459	0.355	0.496	0.145	0.243	0.567	0.244	0.202	0.696	0.239	0.401	0.414
PU7	0.533	0.48	0.584	0.06	0.279	0.588	0.348	0.231	0.751	0.383	0.425	0.394
RI1	0.402	0.332	0.295	0.303	0.161	0.46	0.251	0.1	0.327	0.892	0.3	0.317
RI3	0.364	0.259	0.296	0.143	0.214	0.398	0.211	0.098	0.267	0.893	0.259	0.283
SN1	0.354	0.557	0.451	0.01	0.24	0.476	0.457	0.169	0.602	0.288	0.878	0.435
SN2	0.279	0.384	0.415	0.051	0.219	0.433	0.358	0.046	0.524	0.228	0.78	0.383
SN3	0.321	0.544	0.48	−0.001	0.188	0.395	0.511	0.167	0.564	0.27	0.856	0.453
TR1	0.283	0.39	0.393	−0.123	0.317	0.374	0.523	0.178	0.469	0.211	0.397	0.794
TR2	0.385	0.35	0.493	0.07	0.242	0.485	0.356	0.116	0.505	0.278	0.367	0.768
TR3	0.337	0.285	0.39	−0.059	0.326	0.398	0.376	0.127	0.403	0.247	0.343	0.65
TR4	0.253	0.325	0.295	0.016	0.339	0.241	0.435	−0.01	0.345	0.239	0.367	0.686

Table 3. Comparison of square-rooted AVEs and correlation coefficient analysis

Constructs	FAM	HHC	IU	ODU	PEC	PEOU	POI	PR	PU	RI	SN	TR
FAM	0.726	—	—	—	—	—	—	—	—	—	—	—
HHC	0.482	0.887	—	—	—	—	—	—	—	—	—	—
IU	0.487	0.51	0.796	—	—	—	—	—	—	—	—	—
ODU	0.172	0.036	0.108	0.872	—	—	—	—	—	—	—	—
PEC	0.373	0.3	0.344	0.042	0.793	—	—	—	—	—	—	—
PEOU	0.613	0.456	0.6	0.212	0.343	0.723	—	—	—	—	—	—
POI	0.308	0.515	0.47	−0.057	0.295	0.372	0.807	—	—	—	—	—
PR	0.388	0.253	0.187	0.024	0.296	0.205	0.251	0.802	—	—	—	—
PU	0.475	0.633	0.664	0.054	0.332	0.647	0.518	0.191	0.718	—	—	—
RI	0.429	0.331	0.331	0.25	0.21	0.481	0.259	0.111	0.333	0.893	—	—
SN	0.38	0.593	0.535	0.023	0.257	0.519	0.528	0.154	0.673	0.313	0.839	—
TR	0.44	0.465	0.552	−0.03	0.412	0.531	0.575	0.151	0.602	0.336	0.505	0.727

usefulness has great positive impact on the user's adoption of smart wearable devices. Saeed and Abdinnour-Helm (2,208) further pointed out that perceived usefulness shows pleasant performance in predicting extended usage and exploratory usage at the post adoption stage. This finding implied that perceived usefulness is the key determinant of an intention to use augmented HPDs in the construction environment. Based on this finding, construction practitioners need to pay more efforts on leveraging augmented HPDs to promote on-site safety and efficiency, thereby making sure that workers clearly understand how they would be benefited from the technology. In this regard, strategies such as using augmented HPDs in advance during training sessions or take-home sessions are recommended to strengthen workers' understandings of the technology.

Table 4. Confirmed constructs and corresponding measurement items

Constructs	Measurement items	Interpretation
Perceived ease of use (PEOU)	PEOU1	I would quickly adapt to the use of augmented HPDs at work.
	PEOU 2	Learning to operate augmented HPDs would be easy for me.
	PEOU 3	There is no difficulty for me to understand the working principles of augmented HPDs.
	PEOU 4	Little or no specialized skills and trainings would be required to use augmented HPDs.
	PEOU 5	It would be easy and comfortable to wear augmented HPDs.
Familiarity with the use of AI assistants (FAM)	FAM1	I have heard about other applications of artificial intelligence such as face recognition, voice recognition.
	FAM3	I understand well the strengths and limitations of artificial intelligence.
	FAM4	I would be able to evaluate whether the sound detection results of augmented HPDs are reliable.
	FAM5	Artificial intelligence can sometimes miss important sounds or send wrong alerts.
Hearing health and safety consciousness (HHC)	HHC1	I'm aware of and very concerned about the noises from jobsites that hurt my hearing during my job.
	HHC3	I am concerned about my safety since I am able to hear the environment when using traditional earplugs or earmuffs.
Intention to use (IU)	IU1	I intend to use augmented HPDs if it is provided by my organization.
	IU3	I would prefer to use augmented HPDs under the condition the device is on the mode of reducing all sounds to a safe level, but bypasses and amplifies any critical sounds detected, considering that the system might fail to amplify a critical sound or amplify an unimportant sound.
	IU4	I will encourage field workers who are exposed to hazardous noises to use augmented HPDs for hearing protection.
Openness towards data utilization (ODU)	ODU1	I would be comfortable in letting my colleagues know about my location.
	ODU 2	I would be comfortable in letting safety personnel know when I am in danger condition on a job site.
	ODU 3	I would be comfortable in allowing safety personnel know my responses to the alerts from augmented HPDs.
Perceived economic constraints (PEC)	PEC1	My organization would have the funding to implement augmented HPDs.
	PEC2	The initial cost of augmented HPDs would be high.
	PEC3	The inventory management cost of augmented HPDs would be large.
Perceived organizational impacts (POI)	POI1	The regulations, policies, and procedures on safety in my organization is very strict.
	POI2	Most of my peers working in the field are currently using earplugs or earmuffs whenever required.
	POI3	My peers who use earplugs or earmuffs for hearing protection have shown their demand in improving hearing capability.
Perceived risks (PR)	PR1	There is a possibility of malfunction and performance failure, so they might fail to operate normally.
	PR2	I am concerned that my personal information such as health condition would be unsecured and could be accessed by unauthorized persons, leading to misuse and discrimination.
	PR3	Considering the complexity of ambient sounds, I think there would be a high risk of missing important sounds or sending wrong alerts.
Perceived usefulness (PU)	PU1	Augmented HPDs would make my job easier.
	PU2	Augmented HPDs would improve my productivity.
	PU3	Augmented HPDs would enable me to work safely.
	PU4	Augmented HPDs would allow me to hear safety-critical sounds.
	PU7	Augmented HPDs would reduce project costs.
Resistance to innovation (RI)	RI1	I always want to try new technology.
	RI3	I have a strong interest in innovation.
Subjective norms (SN)	SN1	People who are important to me (family members, relatives, and close friends) would suggest me to use augmented HPDs if they know about it because it would mitigate my job safety risks.
	SN2	My colleagues/peers would suggest me to use augmented HPDs if they know about it because it would mitigate my job safety risks.
	SN3	My supervisors would require me to use augmented HPDs if they know about it because it would mitigate my job safety risks.
Trust (TR)	TR1	I would trust that augmented HPDs devices would do better than humans in terms of recognizing useful sounds at jobsites when being exposed to loud and complex ambient noises.
	TR2	I would trust that augmented HPDs could correctly recognize and block the hazardous sounds.
	TR3	I would trust that augmented HPDs could correctly detect and bypass every important sound to my ears.
	TR4	I would trust that my company would ensure the security and privacy of my personal data.

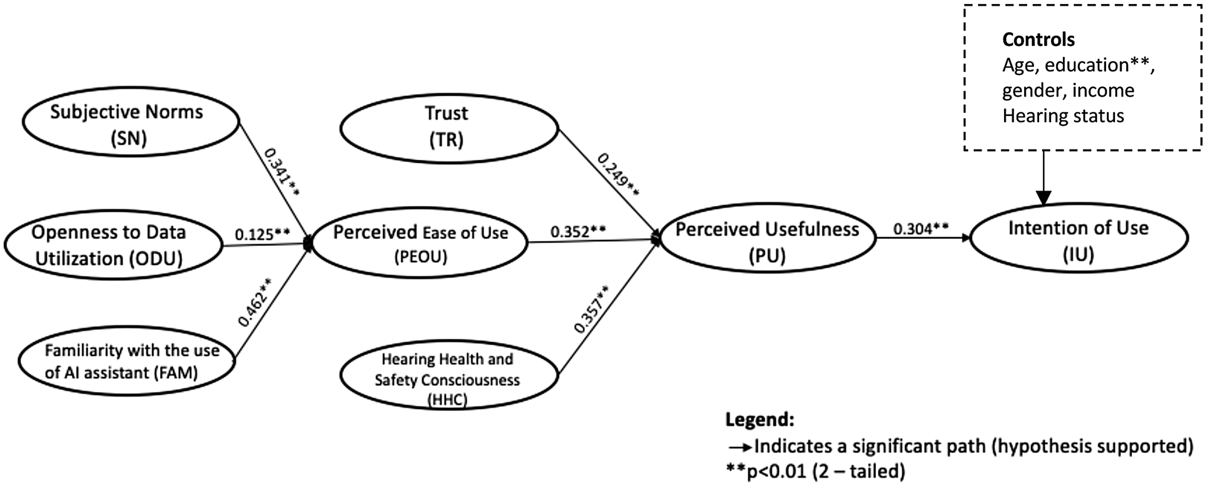

Fig. 3. Tested model with relationships between constructs.

Table 5. Summary of path coefficients and significance levels

Predicted constructs	Hypothesis and corresponding path	β	t-value	Interpretation	R^2
IU	H11: FAM → IU	0.094	1.097	Not supported	0.533
	H13: HHC → IU	0.047	0.636	Not supported	
	H7: ODU → IU	0.044	0.92	Not supported	
	H16: PEC → IU	0.049	0.742	Not supported	
	H2: PEOU à IU	0.183	1.896	Not supported	
	H17: POI → IU	0.088	0.936	Not supported	
	H14: PR → IU	−0.02	0.475	Not supported	
	H1: PU → IU	0.304**	2.92	Supported	
	H15: RI → IU	−0.014	0.23	Not supported	
	H4: SN → IU	0.06	0.621	Not supported	
	H8: TR → IU	0.117	1.277	Not supported	
PEOU	H10: FAM → PEOU	0.462**	7.131	Supported	0.486
	H6: ODU → PEOU	0.125**	2.739	Supported	
	H5: SN → PEOU	0.341**	4.991	Supported	
PU	H3: PEOU → PU	0.352**	5.786	Supported	0.604
	H12: HHC → PU	0.357**	5.696	Supported	
	H9: TR → PU	0.249**	4.314	Supported	
Demographic controls	Gender → IU	−0.025	−0.229	Not supported	—
	Education → IU	0.184*	2.426	Supported	—
	Income → IU	0.066	1.244	Not supported	—
	Age → IU	0.079	0.894	Not supported	—
	Hearing → IU	0.023	0.223	Not Supported	—

Note: $*p < 0.05$ (two-tailed); and $**p < 0.01$ (two-tailed).

Impact of Familiarity with the Use of AI Assistants, Openness toward Data Utilization, and Subjective Norms on Perceived Ease of Use

The results show that there are significant positive correlations between: (1) FAM and PEOU ($\beta = 0.125, \rho < 0.01$); (2) ODU and PEOU ($\beta = 0.125, \rho < 0.01$); and (3) SN and PEOU ($\beta = 0.341, \rho < 0.01$) (Fig. 3 and Table 5). These results indicate that when there are improvements in the familiarity with the use of AI assistants, openness towards data utilization, and subjective norms, construction practitioners feel it easier to use augmented HPDs in their jobs. This finding can be supported by a number of studies (Belanche et al. 2019; Nnaji et al. 2020; Yoon 2009). The study of Belanche et al. (2019) suggested that familiarity with robot, attitude, and SN showed direct effects on PU. In another study by Nnaji et al. (2020), ODU is found to positively influence PEOU. Moreover, as far as the effect of SN is concerned, some studies have pointed out its significant effects (Yoon 2009). Based on such studies, it was implied that FAM, ODU, and SNs are more required when there was less the understanding of such technology. In the context of this study, a possible explanation is that, because AI assistants and the augmented HPDs' direct relation to workers' health and safety are less popular, construction workers would require more FAM, ODU, and SNs in order to feel it easy to use augmented HPDs in their jobs. Based on this finding, future design and adoption of augmented HPDs in construction should consider and address such issues in order to make users feel simple and easy to operate it.

Impact of Perceived Ease of Use, Hearing Health and Safety Consciousness, and Trust on Perceived Usefulness

The results show there are significant positive correlations between: (1) PEOU and PU ($\beta = 0.352, \rho < 0.01$); (2) HHC and PU ($\beta = 0.357, \rho < 0.01$); and (3) TR and PU ($0.249, \rho < 0.01$) (Fig. 3 and Table 5). These results explain the underlying mechanisms by which IU augmented HPDs can be achieved. Because there are no direct influences of PEOU, HHC, and TR on IU augmented HPDs, such influences are fully mediated by perceived usefulness. In order words, the improvements in PEOU, HHC, and TR do not necessarily lead to the higher intention to use augmented HPDs. An intention to use augmented HPDs can be better achieved only when augmented HPDs are perceived as more useful. Therefore, to facilitate the IU augmented HPDs, one should take into account improvements in TR, PEOU, and HHC among construction workers, which in turn will increase the users' perception that the technology is useful. Based on this finding, it is suggested that augmented HPDs can be designed under the premise that users fairly accept the usefulness of the technology, thereby taking further steps that increase users' PEOU, HHC, and TR.

Impact of Demographics on Intention of Use

As shown in Table 5, the examination of education level revealed a significant relationship with the IU AI-based augmented HPDs. The result can be inferred that users holding a higher degree are more likely to accept the technology. This contradicts a previous study on wearable safety technologies conducted by Choi et al. (2017), which reported that no demographic variables affect their adoption. Perhaps more-educated users are more familiar with advanced computational techniques. As a result, they showed a higher willingness in the acceptance of AI assistance in hearing environment sounds when wearing HPDs. This suggests that education and training on AI would be an important strategy to improve the user's adoption. The findings for other demographic variables such as gender, age, and income are consistent with Choi et al. (2017). Our study did not show a significant relationship between these variables and intention to use. Similarly, the present study also did not find a significant relationship between hearing loss status and intention of use augmented HPDs.

Research Contribution

The contributions of the present study are threefold. First this is the first study to examine the factors influencing the IU for augmented hearing protection equipment. Previous studies (Choi et al. 2017; Nnaji et al. 2019; Nnaji and Karakhan 2020) were focused on general safety technologies, thus they do not necessarily reflect the user's intention of use given the novelty and uniqueness of intelligent hearing protection technology. Second, the study expands the existing technology acceptance theories in construction by investigating the user's perceived hearing health and safety and AI-related hypotheses. To the best of our knowledge, no prior studies consider these factors in their models. Our study offers a new understanding that perceived hearing health and workplace safety has a significant impact on the intention of use of hearable devices in construction workplace. This is mediated fully through the perceived usefulness. Also, familiarity with AI shows its strong influence on intention of use through two mediators including perceived ease of use and perceived usefulness. Third, the study contributes new knowledge about the effect of demographic variables on intention of use. Unlike Choi et al. (2017), the present study found a strong relationship between education and IU. This new finding is perhaps due to a unique characteristic of AI-based augmented hearing protection, which differs from other general non-AI safety technologies covered in previous surveys.

To be clear that the scope of this study is focused on developing a single model that can explain the intention of use of AI-based augmented HPDs for users from a diverse background. For that purpose, the study formulated all the hypotheses taking into account the demographic data as control variables. The study was focused on identifying supported hypotheses that are applicable to all subgroups of the population. Thus, the tested model (Fig. 3) included only significant relationships that are true regardless of the user background. The insignificant links found in this study were probably due to the different views from different subgroups of the population. Future research is suggested to conduct cross-group analysis to develop different submodels for different groups of participants.

Conclusions and Limitations

This study envisioned a robust AI-based hearing protection device for construction workers, adopted online survey for data collection, and used the PL-SEM method to explore the relationships between the determinants of workers' acceptance of augmented HPDs. The results of hypotheses testing indicate that perceived usefulness is the only key determinant of users' intention to use augmented HPDs, which indicated that improving users' perceptions on the usefulness of augmented HPDs would greatly contribute to its acceptance. It is also found that perceived usefulness can be improved by three contributing factors, which include PEOU, HHC, and TR, whereas PEOU can be enhanced by SNs, FAM, and ODU. It is therefore recommended that technology developer and construction practitioners need to pay more efforts on leveraging augmented HPDs to promote on-site safety and efficiency, thereby making sure that workers clearly understand how they would be benefited from the technology. This can be achieved through the delivery of synergies, which target PEOU, HHC, TR, SNs, FAM, and ODU in the construction environment.

The findings of this research further enrich the theories of safety technology adoption in construction by identifying the key determinant and its critical contributing factors, including new factors related to health and AI that have not been investigated in previous studies, for promoting the acceptance of the envisioned augmented HPDs and offer a theoretical framework that supports the design and deployment of future envisioned augmented HPDs. Theories of technology adoption in construction deserve further investigation to address the gaps in knowledge, including:

- what are features of augmented HPDs that better meet users' needs?
- how do augmented HPDs address the health and safety challenges brought about by the fourth industrial revolution?
- are there any factors that are important to only a particular subgroup of the population?

Moreover, case studies on the adoption of augmented HPDs on various construction sites may bridge the gaps between theory and practice.

There are a few limitations regarding the data collection of this study. First, the sample size may need to be further extended. However, sample size did not weaken the validity of the research results due to the utilization of both PLS-SEM and bootstrapping. Another limitation was the generalizability of the findings. Despite the questionnaire participants were globally from three different countries in our study, the difference of national culture, legal framework, health and safety regulations, and so on has not been discussed. Such difference may shape the technology acceptance on a new technology.

Appendix. Measurement Items for Demographic Background and Each Construct

Participant demographic background (PDB)	Items	Unit/rating scale
PDB1	Your age.	—
PDB2	Where are you based in? Country and state or province (e.g., US, SC).	—
PDB3	Your gender.	1 = female, 2 = male
PDB4	Your race/ethnicity.	1 = white, 2 = Hispanic or Latino, 3 = Black or African American, 4 = Native American or American Indian, 5 = Asian/ Pacific Islander, 6 = other
PDB5	Your annual income.	1 = less than \$25,000; 2 = \$25,000–\$50,000; 3 = \$50,000–\$100,000; 4 = \$100,000–\$200,000; 5 = more than \$200,000
PDB6	Your final education level.	1 = less than high school, 2 = high school, 3 = Bachelor, 4 = Master, 5 = Ph.D. holder
PDB7	Your job title.	—
PDB8	Do you think you are experiencing physical hearing loss?	1 = I totally disagree, 5 = I totally agree
PDB9	Are you exposed to noise during your job?	1 = I totally disagree, 5 = I totally agree
PDB10	I have heard about injury, deaths, or any forms of loss caused by the use of hearing protection.	1 = No, 2 = Yes
PDB11	I always use hearing protection devices whenever there is hazardous noise on the jobsite.	1 = I totally disagree, 5 = I totally agree
Constructs and measurement items	*Interpretation*	*Unit/rating scale*
Perceived ease of use (PEOU)	The degree to which a person believes that augmented HPDs would be easy to use.	—
PEOU1	I would quickly adapt to the use of augmented HPDs at work.	1 = I totally disagree, 5 = I totally agree
PEOU2	Learning to operate augmented HPDs would be easy for me.	1 = I totally disagree, 5 = I totally agree
PEOU3	There is no difficulty for me to understand the working principles of augmented HPDs.	1 = I totally disagree, 5 = I totally agree
PEOU4	Little or no specialized skills and trainings would be required to use augmented HPDs.	1 = I totally disagree, 5 = I totally agree
PEOU5	It would be easy and comfortable to wear augmented HPDs.	1 = I totally disagree, 5 = I totally agree
Subjective Norms (SNs)	Perception of important (or relevant) others' beliefs about my use of augmented HPDs	—
SN1	People who are important to me (family members, relatives, and close friends) would suggest me to use augmented HPDs if they know about it because it would mitigate my job safety risks.	1 = I totally disagree, 5 = I totally agree
SN2	My colleagues/peers would suggest me to use augmented HPDs if they know about it because it would mitigate my job safety risks.	1 = I totally disagree, 5 = I totally agree
SN3	My supervisors would require me to use augmented HPDs if they know about it because it would mitigate my job safety risks.	1 = I totally disagree, 5 = I totally agree
Resistance to innovation (RI)	The extent to which an individual resists new technology	—
RI1	I always want to try new technology.	1 = I totally disagree, 5 = I totally agree
RI2	I often try a new technology when many colleagues/friends of mine have already tried.	1 = I totally disagree, 5 = I totally agree
RI3	I have a strong interest in innovation.	1 = I totally disagree, 5 = I totally agree
Openness to data utilization (ODU)	The extent to which an individual is comfortable with their data of job conditions being used and shared by a certain group while using augmented HPDs.	—
ODU1	I would be comfortable in letting my colleagues know about my location.	1 = I totally disagree, 5 = I totally agree
ODU2	I would be comfortable in letting safety personnel know when I am in danger condition on a job site.	1 = I totally disagree, 5 = I totally agree
ODU3	I would be comfortable in allowing safety personnel know my responses to the alerts from augmented HPDs.	1 = I totally disagree, 5 = I totally agree
Hearing health and safety consciousness (HHC)	Awareness and care of hearing health conditions, and the degree to which hearing health concerns are integrated into an individual's regular work.	—
HHC1	I'm aware of and very concerned about the noises from jobsites that hurt my hearing during my job.	1 = I totally disagree, 5 = I totally agree
HHC2	I would make efforts to manage my hearing health during my job.	1 = I totally disagree, 5 = I totally agree
HHC3	I am concerned about my safety since I am able to hear the environment when using traditional earplugs or earmuffs.	1 = I totally disagree, 5 = I totally agree
Perceived economic constraints (PEC)	Perception of the economic constraints or consideration of using augmented HPDs.	This group of question is for business leaders
PEC1	My organization would have the funding to implement augmented HPDs.	1 = I totally disagree, 5 = I totally agree
PEC2	The initial cost of augmented HPDs would be high.	1 = I totally disagree, 5 = I totally agree
PEC3	The inventory management cost of augmented HPDs would be large.	1 = I totally disagree, 5 = I totally agree

Appendix. (*Continued.*)

Participant demographic background (PDB)	Items	Unit/rating scale
Perceived behavioral control (PBC)	Perception of ability to perform augmented HPDs.	—
PBC1	I am confident that I could perform augmented HPDs.	1 = I totally disagree, 5 = I totally agree
PBC2	Whether I perform augmented HPDs or not is not entirely up to me.	1 = I totally disagree, 5 = I totally agree
Familiarity with the use of AI assistants (FAM)	The degree to which the user is familiar with AI assistants.	—
FAM1	I have heard about other applications of artificial intelligence such as face recognition, voice recognition.	1 = I totally disagree, 5 = I totally agree
FAM2	I have used artificial intelligence assistance.	1 = I totally disagree, 5 = I totally agree
FAM3	I understand well the strengths and limitations of artificial intelligence.	1 = I totally disagree, 5 = I totally agree
FAM4	I would be able to evaluate whether the sound detection results of augmented HPDs are reliable.	1 = I totally disagree, 5 = I totally agree
FAM5	Artificial intelligence will never miss important sounds or send wrong alerts.	1 = I totally disagree, 5 = I totally agree
Perceived risks (PRs)	A combination of uncertainty and seriousness of an outcome in relation to performance, safety, psychological or social uncertainties.	—
PR1	There is a possibility of malfunction and performance failure, so they might fail to operate normally.	1= I totally disagree, 5= I totally agree
PR2	I am concerned that my personal information such as health condition would be unsecured and could be accessed by unauthorized persons, leading to misuse and discrimination.	1 = I totally disagree, 5 = I totally agree
PR3	Considering the complexity of ambient sounds, I think there would be a high risk of missing important sounds or sending wrong alerts.	1 = I totally disagree, 5 = I totally agree
Intention to use (IU)	An individual's motivation or willingness to exert effort to use augmented HPDs.	—
IU1	I intend to use augmented HPDs if it is provided by my organization.	1 = I totally disagree, 5 = I totally agree
IU2	I would prefer to use augmented HPDs under the condition the device is on the mode of blocking all sounds to my ears and sending me an alert if a hazard event is detected, considering that the system might miss an important sound or send a wrong alert.	1 = I totally disagree, 5 = I totally agree
IU3	I would prefer to use augmented HPDs under the condition the device is on the mode of reducing all sounds to a safe level, but bypasses and amplifies any critical sounds detected, considering that the system might fail to amplify a critical sound or amplify an unimportant sound.	1 = I totally disagree, 5 = I totally agree
IU4	I will encourage field workers who are exposed to hazardous noises to use augmented HPDs for hearing protection.	1 = I totally disagree, 5 = I totally agree

Data Availability Statement

The survey dataset collected or used during the study is available from the corresponding author by request.

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References

Adapa, A., F. F. H. Nah, R. H. Hall, K. Siau, and S. N. Smith. 2018. "Factors influencing the adoption of smart wearable devices." *Int. J. Hum.-Comput. Interact.* 34 (5): 399–409. https://doi.org/10.1080/10447318.2017.1357902.

Ahadzadeh, A. S., S. P. Sharif, F. S. Ong, and K. W. Khong. 2015. "Integrating health belief model and technology acceptance model: An investigation of health-related internet use." *J. Med. Internet Res.* 17 (2): e45. https://doi.org/10.2196/jmir.3564.

Ahuja, V., J. Yang, and R. Shankar. 2009. "Study of ICT adoption for building project management in the Indian construction industry." *Autom. Constr.* 18 (4): 415–423. https://doi.org/10.1016/j.autcon.2008.10.009.

Ajzen, I. 1991. "The theory of planned behavior." *Organizational Behav. Hum. Decis. Processes* 50 (2): 179–211. https://doi.org/10.1016/0749-5978(91)90020-T.

Belanche, D., L. V. Casaló, and C. Flavián. 2019. "Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers." *Ind. Manage. Data Syst.* 119 (7): 1411–1430. https://doi.org/10.1108/IMDS-08-2018-0368.

Bentler, P. M., and W. Huang. 2014. "On components, latent variables, PLS and simple methods: Reactions to Rigdon's rethinking of PLS." *Long Range Plann.* 47 (3): 138–145. https://doi.org/10.1016/j.lrp.2014.02.005.

Bernard, H. R., and H. R. Bernard. 2013. *Social research methods: Qualitative and quantitative approaches*. Los Angeles: SAGE.

Bernstein, E. R., A. J. Brammer, and G. Yu. 2013. "Improving speech understanding in communication headsets: Simulation of adaptive subband processing for speech in noise." *Int. J. Ind. Ergon.* 43 (6): 526–535. https://doi.org/10.1016/j.ergon.2012.10.004.

Bernstein, E. R., A. J. Brammer, and G. Yu. 2014. "Augmented warning sound detection for hearing protectors." *J. Acoust. Soc. Am.* 135 (1): EL29–EL34. https://doi.org/10.1121/1.4835135.

Bhattacherjee, A., and N. Hikmet. 2007. "Physicians' resistance toward healthcare information technology: A theoretical model and empirical test." *Eur. J. Inf. Syst.* 16 (6): 725–737. https://doi.org/10.1057/palgrave.ejis.3000717.

Buhrmester, M., T. Kwang, and S. D. Gosling. 2016. "Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality data?" In *Methodological issues and strategies in clinical research*, edited by A. E. Kazdin, 133–139. Washington, DC: American Psychological Association.

Casali, J. G. 2010. "Powered electronic augmentations in hearing protection technology circa 2010 including active noise reduction, electronically-modulated sound transmission, and tactical communications devices: Review of design, testing, and research." *Int. J. Acoust. Vibr.* 15 (4): 168.

Casali, J. G., and M. B. Robinette. 2015. "Effects of user training with electronically-modulated sound transmission hearing protectors and the open ear on horizontal localization ability." Supplement, *Int. J. Audiology* 54 (S1): S37–S45. https://doi.org/10.3109/14992027.2014.973538.

Casali, J. G., G. S. Robinson, E. C. Dabney, and D. Gauger. 2004. "Effect of electronic ANR and conventional hearing protectors on vehicle backup alarm detection in noise." *Hum. Factors* 46 (1): 1–10. https://doi.org/10.1518/hfes.46.1.1.30387.

Cheng, C. F., A. Rashidi, M. A. Davenport, and D. V. Anderson. 2017. "Activity analysis of construction equipment using audio signals and support vector machines." *Autom. Constr.* 81 (Sep): 240–253. https://doi.org/10.1016/j.autcon.2017.06.005.

Choi, B., S. Hwang, and S. Lee. 2017. "What drives construction workers' acceptance of wearable technologies in the workplace? Indoor localization and wearable health devices for occupational safety and health." *Autom. Constr.* 84 (Dec): 31–41. https://doi.org/10.1016/j.autcon.2017.08.005.

Clasing, J. E., and J. G. Casali. 2014. "Warfighter auditory situation awareness: Effects of augmented hearing protection/enhancement devices and TCAPS for military ground combat applications." Supplement, *Int. J. Audiology* 53 (S2): S43–S52. https://doi.org/10.3109/14992027.2013.860489.

Clavel, C., T. Ehrette, and G. Richard. 2005. "Events detection for an audio-based surveillance system." In *Proc., 2005 IEEE Int. Conf. on Multimedia and Expo*, 1306–1309. New York: IEEE.

CPWR (Center for Construction Research and Training). n.d. *Noise-induced hearing loss in construction and other industries*. Silver Spring, MD: CPWR.

Cramer, J., H. H. Wu, J. Salamon, and J. P. Bello. (2019). "Look, listen, and learn more: Design choices for deep audio embeddings." In *Proc., ICASSP, IEEE Int. Conf. on Acoustics, Speech and Signal Processing*, 3852–3856. New York: IEEE.

Davis, F. D. 1993. "User acceptance of information technology: System characteristics, user perceptions and behavioral impacts." *Int. J. Man Mach. Stud.* 38 (3): 475–487. https://doi.org/10.1006/imms.1993.1022.

Davison, A. C., and D. V. Hinkley. 1997. *Bootstrap methods and their application*. Cambridge, UK: Cambridge Univ. Press.

Deshaies, P., et al. 2015. "Noise as an explanatory factor in work-related fatality reports." *Noise Health* 17 (78): 294. https://doi.org/10.4103/1463-1741.165050.

Dou, K., P. Yu, N. Deng, F. Liu, Y. Guan, Z. Li, Y. Ji, N. Du, X. Lu, and H. Duan. 2017. "Patients' acceptance of smartphone health technology for chronic disease management: A theoretical model and empirical test." *JMIR Mhealth Uhealth* 5 (12): e177. https://doi.org/10.2196/mhealth.7886.

Efron, B., and R. Tibshirani. 1986. "Bootstrap methods for standard errors, confidence intervals, and other measures of statistical accuracy." *Stat. Sci.* 1 (1): 54–75. https://doi.org/10.1214/ss/1177013815.

Egea, J. M. O., and M. V. R. González. 2011. "Explaining physicians' acceptance of EHCR systems: An extension of TAM with trust and risk factors." *Comput. Hum. Behav.* 27 (1): 319–332. https://doi.org/10.1016/j.chb.2010.08.010.

Falk, R. F., and N. B. Miller. 1992. *A primer for soft modeling*. Akron, OH: Univ. of Akron Press.

Fang, D., C. Zhao, and M. Zhang. 2016. "A cognitive model of construction workers' unsafe behaviors." *J. Constr. Eng. Manage.* 142 (9): 04016039. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001118.

Feng, Y., and M. T. Trinh. 2019. "Developing resilient safety culture for construction projects." *J. Constr. Eng. Manage.* 145 (11): 04019069. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001720.

Feng, Y., P. Wu, G. Ye, and D. Zhao. 2017. "Risk-compensation behaviors on construction sites: Demographic and psychological determinants." *J. Manage. Eng.* 33 (4): 04017008. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000520.

Fornell, C., and F. L. Bookstein. 1982. "Two structural equation models: LISREL and PLS applied to consumer exit-voice theory." *J. Marketing Res.* 19 (4): 440–452. https://doi.org/10.1177/002224378201900406.

Fornell, C., and D. F. Larcker. 1981. "Structural equation models with unobservable variables and measurement error: Algebra and statistics." *J. Marketing Res.* 382–388. https://doi.org/10.1177/002224378101800313.

Gaston, J., A. Foots, T. Mermagen, and A. Scharine. 2018. "The effectiveness of tactical communication and protection systems (TCAPS) on minimizing hearing hazard and maintaining auditory situational awareness." In *Proc., Int. Conf. on Applied Human Factors and Ergonomics*, 382–391. Cham, Switzerland: Springer.

Giguère, C., C. Laroche, A. J. Brammer, V. Vaillancourt, and G. Yu. 2011. "Advanced hearing protection and communication: Progress and challenges." In *Proc., 11th Int. Congress on Noise as a Public Health Problem*, 24–28. Milton Keynes: Institute of Acoustics.

Giguère, C., C. Laroche, and V. Vaillancourt. 2013. "Advanced hearing protection and auditory awareness in individuals with hearing loss." In *Proc., of Meetings on Acoustics ICA2013*, 040010. Melville, NY: Acoustical Society of America.

Girard, S.-A., T. Leroux, M. Courteau, M. Picard, F. Turcotte, and O. Richer. 2015. "Occupational noise exposure and noise-induced hearing loss are associated with work-related injuries leading to admission to hospital." *Inj. Prev.* 21 (e1): e88–e92. https://doi.org/10.1136/injuryprev-2013-040828.

Gunzler, D., T. Chen, P. Wu, and H. Zhang. 2013. "Introduction to mediation analysis with structural equation modeling." *Shanghai Arch. Psychiatry* 25 (6): 390.

Hair, J. F., Jr., G. T. M. Hult, C. Ringle, and M. Sarstedt. 2016. *A primer on partial least squares structural equation modeling (PLS-SEM)*. Los Angeles: SAGE.

Hair, J. F., C. M. Ringle, and M. Sarstedt. 2013. "Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance." *Long Range Plann.* 46 (1–2): 1–12. https://doi.org/10.1016/j.lrp.2013.01.001.

Hsieh, P.-J. 2015. "Healthcare professionals' use of health clouds: Integrating technology acceptance and status quo bias perspectives." *Int. J. Med. Inf.* 84 (7): 512–523. https://doi.org/10.1016/j.ijmedinf.2015.03.004.

Huang, Y., and T. Le. 2020. *Factors affecting the implementation of AI-based hearing protection technology at construction workplace*. London: International Association for Automation and Robotics in Construction. https://doi.org/10.22260/ISARC2020/0140.

Hwang, S., and S. Lee. 2017. "Wristband-type wearable health devices to measure construction workers' physical demands." *Autom. Constr.* 83 (Nov): 330–340. https://doi.org/10.1016/j.autcon.2017.06.003.

Im, I., Y. Kim, and H.-J. Han. 2008. "The effects of perceived risk and technology type on users' acceptance of technologies." *Inf. Manage.* 45 (1): 1–9. https://doi.org/10.1016/j.im.2007.03.005.

Kock, N. 2011. "Using WarpPLS in e-collaboration studies: Mediating effects, control and second order variables, and algorithm choices." *Int. J. e-Collab.* 7 (3): 1–13. https://doi.org/10.4018/jec.2011070101.

Kurkovsky, O. R., O. Rivera, and J. Bhalodi. 2007. "Classification of privacy management techniques in pervasive computing." *Int. J. u-and e-Serv. Sci. Technol.* 11 (1): 55–71.

Lee, Y.-C., M. Scarpiniti, and A. Uncini. 2020a. "Advanced sound classifiers and performance analyses for accurate audio-based construction project monitoring." *J. Comput. Civ. Eng.* 34 (5): 04020030. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000911.

Lee, Y.-C., M. Shariatfar, A. Rashidi, and H. W. Lee. 2020b. "Evidence-driven sound detection for prenotification and identification of construction safety hazards and accidents." *Autom. Constr.* 113 (May): 103127. https://doi.org/10.1016/j.autcon.2020.103127.

Lee, Y.-H., Y.-C. Hsieh, and C.-N. Hsu. 2011. "Adding innovation diffusion theory to the technology acceptance model: Supporting employees' intentions to use e-learning systems." *J. Educ. Technol. Soc.* 14 (4): 124–137.

Lohmöller, J.-B. 2013. *Latent variable path modeling with partial least squares*. Berlin: Springer.

Mlynski, R., and E. Kozlowski. 2019. "Localization of vehicle back-up alarms by users of level-dependent hearing protectors under industrial noise conditions generated at a forge." *Int. J. Environ. Res. Public Health* 16 (3): 394. https://doi.org/10.3390/ijerph16030394.

Morata, T. C., C. L. Themann, R. F. Randolph, B. L. Verbsky, D. C. Byrne, and E. R. Reeves. 2005. "Working in noise with a hearing loss: Perceptions from workers, supervisors, and hearing conservation program managers." *Ear Hear.* 26 (6): 529–545. https://doi.org/10.1097/01.aud.0000188148.97046.b8.

Mun, Y. Yi, J. D. Jackson, J. S. Park, and J. C. Probst. 2006. "Understanding information technology acceptance by individual professionals: Toward an integrative view." *Inf. Manage.* 43 (3): 350–363. https://doi.org/10.1016/j.im.2005.08.006.

Nakashima, A., and K. McDavid. 2018. "Protecting the hearing-impaired worker: Speech understanding with electronic hearing protection devices." *J. Mil. Veteran Family Health* 4 (1): 42–50. https://doi.org/10.3138/jmvfh.2017-0018.

NIOSH (National Institute for Occupational Safety & Health). 2019. *National occupational research agenda for hearing loss prevention*. Washington, DC: NIOSH.

Nnaji, C., J. Gambatese, A. Karakhan, and C. Eseonu. 2019. "Influential safety technology adoption predictors in construction." *Eng. Constr. Archit. Manage.* 26 (11): 2655–2681. https://doi.org/10.1108/ECAM-09-2018-0381.

Nnaji, C., J. Gambatese, A. Karakhan, and R. Osei-Kyei. 2020. "Development and application of safety technology adoption decision-making tool." *J. Constr. Eng. Manage.* 146 (4): 04020028 https://doi.org/10.1061/(ASCE)CO.1943-7862.0001808.

Nnaji, C., and A. A. Karakhan. 2020. "Technologies for safety and health management in construction: Current use, implementation benefits and limitations, and adoption barriers." *J. Build. Eng.* 29 (May): 101212. https://doi.org/10.1016/j.jobe.2020.101212.

Pantelopoulos, A., and N. G. Bourbakis. 2009. "A survey on wearable sensor-based systems for health monitoring and prognosis." *IEEE Trans. Syst. Man Cybern. Part C Appl. Rev.* 40 (1): 1–12. https://doi.org/10.1109/TSMCC.2009.2032660.

Park, Y., H. Son, and C. Kim. 2012. "Investigating the determinants of construction professionals' acceptance of web-based training: An extension of the technology acceptance model." *Autom. Constr.* 22 (Mar): 377–386. https://doi.org/10.1016/j.autcon.2011.09.016.

Peansupap, V., and D. Walker. 2005. "Exploratory factors influencing information and communication technology diffusion and adoption within Australian construction organizations: A micro analysis." *Constr. Innovation* 5 (3): 135–157. https://doi.org/10.1108/14714170510815221.

Salamon, J., and J. P. Bello. 2017. "Deep convolutional neural networks and data augmentation for environmental sound classification." *IEEE Signal Process. Lett.* 24 (3): 279–283. https://doi.org/10.1109/LSP.2017.2657381.

Salamon, J., C. Jacoby, and J. P. Bello. 2014. "A dataset and taxonomy for urban sound research." In *Proc., MM 2014—Proc. of the 2014 ACM Conf. on Multimedia*, 1041–1044. New York: Association for Computing Machinery.

Saleem, A. H., G. Alkharboush, O. Almazyed, S. AlHilal, I. Alnajashi, T. Al-Andejani, M. Al Momani, and A. Hagr. 2018. "Prevalence of hearing loss and tinnitus with correlation to the usage of protective hearing equipment among airport workers." *J. Nat. Sci. Med.* 1 (1): 31.

Schifter, D. E., and I. Ajzen. 1985. "Intention, perceived control, and weight loss: An application of the theory of planned behavior." *J. Personality Social Psychol.* 49 (3): 843. https://doi.org/10.1037/0022-3514.49.3.843.

Seixas, N., and R. Neitzel. 2004. *Noise exposure and hearing protection use among construction workers in Washington State*. Seattle: Dept. of Environmental and Occupational Health Sciences.

Smalt, C. J., P. T. Calamia, A. P. Dumas, J. P. Perricone, T. Patel, J. Bobrow, P. P. Collins, M. L. Markey, and T. F. Quatieri. 2020. "The effect of hearing-protection devices on auditory situational awareness and listening effort." *Ear Hear.* 41 (1): 82–94. https://doi.org/10.1097/AUD.0000000000000733.

Son, H., S. Lee, and C. Kim. 2015. "What drives the adoption of building information modeling in design organizations? An empirical investigation of the antecedents affecting architects' behavioral intentions." *Autom. Constr.* 49 (Jan): 92–99. https://doi.org/10.1016/j.autcon.2014.10.012.

Vacher, M., D. Istrate, L. Besacier, J.-F. Serignat, E. Castelli, and L. Besacier. 2004. "Sound detection and classification for medical telesurvey." In *Proc., 2nd Conf. on Biomedical Engineering*. Calgary, AB, Canada: ACTA Press.

Ye, T., J. Xue, M. He, J. Gu, H. Lin, B. Xu, and Y. Cheng. 2019. "Psychosocial factors affecting artificial intelligence adoption in health care in China: Cross-sectional study." *J. Med. Internet Res.* 21 (10): e14316. https://doi.org/10.2196/14316.

Yoon, C. 2009. "The effects of national culture values on consumer acceptance of e-commerce: Online shoppers in China." *Inf. Manage.* 46 (5): 294–301. https://doi.org/10.1016/j.im.2009.06.001.

Young, F., L. Zhang, R. Jiang, H. Liu, and C. Wall. 2020. "A deep learning based wearable healthcare IoT device for ai-enabled hearing assistance automation." Preprint, submitted May 16, 2020. http://arxiv.org/abs/2005.08076.

Young, J. E., R. Hawkins, E. Sharlin, and T. Igarashi. 2009. "Toward acceptable domestic robots: Applying insights from social psychology." *Int. J. Social Rob.* 1 (1): 95. https://doi.org/10.1007/s12369-008-0006-y.

Zack, J. 2016. "Trends in construction technology: The potential impact on project management and construction claims." In *A research perspective*. Chicago: The Navigant Construction Forum.

Zhang, P., and F. F. Ng. 2013. "Explaining knowledge-sharing intention in construction teams in Hong Kong." *J. Constr. Eng. Manage.* 139 (3): 280–293. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000607.