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Digital Technology Knowledge Transfer Enablers Amongst End-Users in Architecture, Engineering, and Construction Organisations: New Zealand Insights

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Abstract: The architecture, engineering, and construction (AEC) sectors are constantly evolving, and the effective adoption and use of digital technologies are critical for improving project outcomes, enhancing productivity, and fostering innovation. This study aims to identify and analyse the key factors that enable effective knowledge transfer among digital technology end-users in the AEC industry. The study's theoretical framework is a modified version of the technology acceptance model (TAM). It investigates six knowledge transfer enablers, including ease of use, perceived usefulness, training and support, self-efficacy, and mastery goal orientation. The study also examines the mediating roles of transfer motivation in the relationship between these enablers and knowledge transfer effectiveness. A quantitative research methodology was employed to conduct the research, using partial least squares structural equation modelling (PLS-SEM) to analyse data collected from 85 construction practitioners through an online survey. The study reveals that there are significant positive relationships between the knowledge transfer enablers and the effectiveness of knowledge transfer, with transfer motivation playing a crucial mediating role. Self-efficacy is the single most important driver of digital technology (DT) knowledge transfer, while supervisory support has a marginal role. Mastery goal orientation increases an employee's knowledge transfer motivations; therefore, challenging working environments have a positive influence on DT knowledge transfer. These results contribute to the theoretical understanding of knowledge transfer in the context of digital technology use in AEC organisations. The study provides practical insights for managers and policymakers on creating an environment that facilitates effective knowledge transfer, emphasising the need for supportive organisational cultures, adequate training, and the development of user-friendly and compatible technologies. It further highlights the importance of motivating end-users to participate in knowledge transfer processes and suggests strategies to enhance motivation, leading to the successful adoption and utilisation of digital technologies in the AEC industry.

Keywords: AEC; digital technology; enablers; knowledge transfer; motivation

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1. Introduction

The construction industry has historically been slow to adopt and integrate digital technologies, lagging behind other economic sectors [1,2]. However, recent advances in digital technologies such as building information modelling (BIM), virtual and augmented reality (VR/AR), and the Internet of Things (IoT) have created new opportunities for the industry to improve efficiency, productivity, and safety in construction [3–5]. According to Bryde et al. [6] and Herr and Fisher [7], digital technologies can facilitate collaboration amongst stakeholders, including designers, engineers, contractors, and owners, improving communication and decision-making throughout the project lifecycle.

The construction industry faces significant challenges in the adoption and integration of digital technologies despite their potential benefits. Gholami [8] suggests that adoption challenges are due to the lack of understanding in identifying, assessing, and selecting appropriate technologies. The ease with which digital technologies can be learned and used seems to be a critical influencing factor [9]. Furthermore, factors such as organisational culture, the perceived value of technology investments, and the availability of skilled personnel capable of leveraging these technologies constrain the uptake of these technologies [10]. Moreover, the unique characteristics of the construction industry, including the complexity of project activities, site-specific constraints, and the temporary and fragmented nature of construction teams, are major impediments to the seamless integration of digital tools [11]. Therefore, the complex and ad hoc nature of digital technology adoption in construction underscores the need for a more systematic approach to decisions regarding the differential pace of digital technology adoption in the construction industry [5,8]. The successful adoption and implementation of digital technologies hinge on effective knowledge transfer among end-users [12,13].

This study presents a modified version of the technology acceptance model (TAM) [14], which has been adapted by various authors since 1983 to align with their research on technology acceptance and integration. The model emphasises that the perceived usefulness and ease of use of a technology are crucial factors influencing its adoption and usage by individuals. Moreover, the existing literature highlights the significance of these factors in digital technology knowledge transfer. In contrast to the TAM's introduction of behavioural intention to use as a link between determinants and actual technology usage, the modified version incorporates 'transfer motivation' as a mediator between knowledge transfer and its determinants. This implies that the motivation or intention to transfer, developed through its determinants, can serve as a catalyst for effective knowledge transfer. By applying this model in the construction industry, insights can be gained into the specific obstacles and facilitators influencing the uptake of digital technology among industry professionals.

The availability of skilled personnel capable of leveraging digital technologies is central to the adoption and integration of these technologies in the AEC sectors. Therefore, training programmes tailored to the unique needs of the construction industry can bridge the gap between the potentials of digital technologies and their actual implementation [15]. Such programmes should not only focus on the technical aspects of digital tools but also emphasise the importance of collaboration, project management, and data analytics in a manner that reflects the multifaceted nature of construction projects.

The dissemination of digital technology knowledge within organisations is significant. Trainees, having acquired new skills and insights, are positioned to act as change agents, fostering a culture of innovation and continuous improvement within organisations. This peer-to-peer knowledge transfer can accelerate the diffusion of digital technologies across different organisational levels, enhancing overall competitiveness and efficiency [16,17]. However, for the desired knowledge to be transferred, organisations must create environments that encourage sharing and collaboration amongst organisation members, recognising and rewarding individuals who contribute to the collective digital proficiency of their work teams. Organisations should consider digital technologies as strategic investments that can enhance their efficiency, productivity, and safety performance in construction projects. For example, BIM and the IoT can provide real-time data to project stakeholders, enabling informed decision-making throughout the project lifecycle [18]. Furthermore, the integration of digital technologies can improve safety in construction projects by enabling the identification and mitigation of safety hazards [19], and it can also enhance sustainable performance [3]. Digital technologies such as VR/AR can provide immersive training for workers, enabling them to acquire new skills and insights in a safe and controlled environment [20]. Thus, the literature suggests that AEC leadership should provide the necessary resources to support the adoption and integration of digital technologies and promote a culture of innovation and continuous improvement [11,21].

The unique characteristics possessed by the AEC sectors, such as multi-faceted practice, organisational culture, the perceived value of technology investments, and the unavailability of skilled personnel, pose challenges to digital technology uptake. Therefore, the key question being addressed within the current study is the following: how does digital technology transfer occur within AEC organisations considering the challenges posed by the sectors' unique characteristics? Thus, this study aims to explore the dynamics of digital technology adoption and integration within these sectors, utilising the modified TAM as a framework for the investigation. Through the analysis of behavioural intentions, organisational members' motivation, and digital technology usage factors contained in the TAM, the study can provide insights into the transfer of digital technology knowledge amongst end-users in the AEC industry.

2. Theoretical Framework and Model Development

Knowledge transfer as a concept is not new, but an understanding of the concept within the unique context of AEC organisations presents distinct challenges and opportunities, moreso with the exploration of the adoption and integration of digital technologies within AEC organisations. The literature establishes the significance of organisational culture and technology acceptance in either facilitating or hindering knowledge transfer [22,23]. On the other hand, Krogh et al. [24] emphasise the impact of leadership on interactions between individuals on knowledge creation (and promotion; Yap & Toh, [25]) processes within organisations. Takhtravanchi and Pathirage [26]) posit that capturing, sharing, and transferring knowledge within the AEC sector is complex, especially in traditionally procured construction projects. There are also complexities arising from technical and management intricacies that affect knowledge transfer among innovation subjects in mega-project settings [27]. Yet, there is a progressive recognition of knowledge as a strategic asset that needs to be captured, disseminated, and applied within AEC organisations [28].

2.1. Digital Technology Knowledge Transfer (DTKT)

Knowledge transfer encompasses a wide scope of activities. In this study, DTKT refers to the activities related to DT knowledge-sharing and accepting (i.e., adopting or receiving) or disseminating. Suksa-Ngiam and Chaiyasoonthorn [29] and Nguyen and Fry [30] have conducted empirical studies that help in identifying specific factors that can either enable or hinder digital technology knowledge transfer. These factors include technology infrastructure, trust among peers, and the organisational reward system. Additionally, theoretical frameworks provided by Burke and Hutchins [31] and Chiaburu and Marinova [32], along with the empirical findings of Sitzmann and Ely [33] and Yan et al. [34], also enrich the understanding of the psychological and social dynamics that drive knowledge-sharing behaviours. Furthermore, Senko [35] and Saini et al. [36] highlight the role of individual motivation and cognitive processes in knowledge transfer. These studies collectively underscore the multifaceted nature of knowledge transfer in AEC organisations, influenced by a confluence of individual, organisational, and environmental factors. Thus, an examination of knowledge transfer enablers among digital technology end-users in AEC organisations could provide a nuanced understanding of the complexities involved in fostering an environment conducive to knowledge-sharing and learning, thereby contributing to the body of knowledge in the field of AEC. Digital technology encompasses a wide range of tools and systems, including building information modelling (BIM), geographic information systems (GISs), project management software, and various simulation and analysis tools [37,38]. These technologies offer the promise of streamlined project workflows, enhanced collaboration, and improved accuracy and efficiency. Yet, the full realisation of these benefits is contingent upon the effective transfer of knowledge among professionals within the AEC sector. Knowledge transfer is critical not only for the initial adoption of these technologies but also for their continued effective use and evolution. Therefore, this study draws on the extant literature connected to the TAM and beyond, where there exists an understanding of individual behaviours within organisational settings in the context of the transfer of knowledge of digital technologies in AEC organisations. The developed theoretical model (see Figure 1) has three key dimensions that explain the interplay between technology transfer enablers, namely self-efficacy, perceived ease of use, mastery goal orientation, supervisory support, and peer support and use of technology; individuals' transfer motivation; and digital technology knowledge transfer. Being in line with the underpinning theoretical framework with the intention to use it as an intermediary driver for the actual technology usage, this model introduces transfer motivation as a mediating variable that explains the relationship between the six technology transfer enablers and digital knowledge transfer. The items captured within the transfer motivation construct adopted by this study adequately represent the intention to use digital technologies in the construction industry (full details of the model constructs and their indicators are provided in Appendix A). The next section explains the theoretical background of each variable and the hypotheses related to the direct and indirect relationships identified by the model (Figure 1).

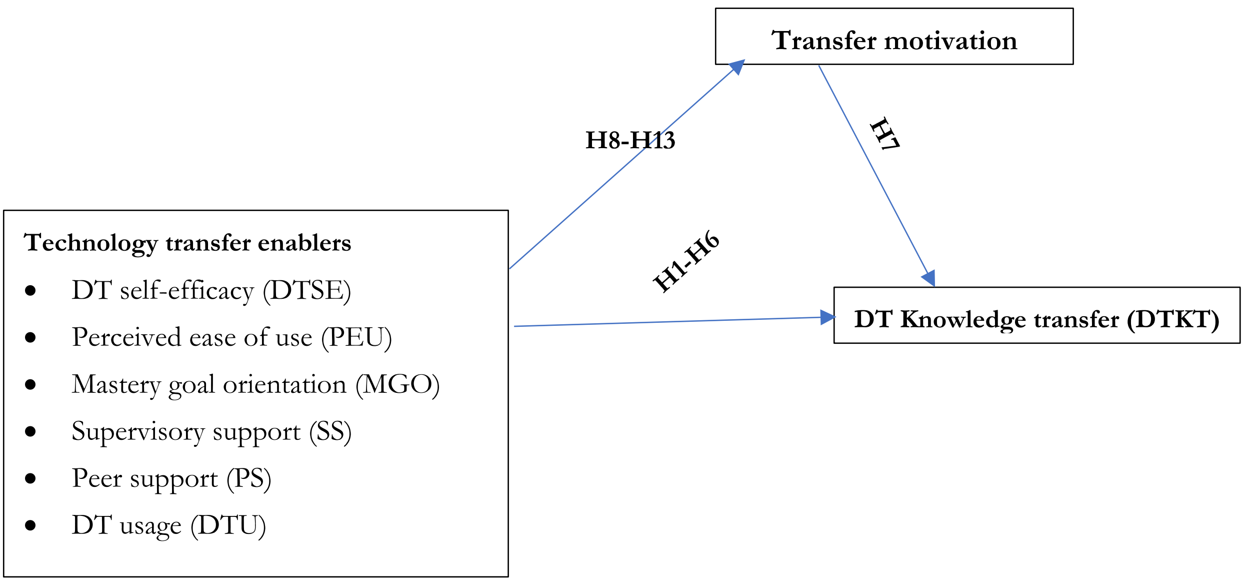

Figure 1. Theoretical research model.

2.2. Digital Self-Efficacy (DTSE)

Self-efficacy, introduced by Bandura [39], is pivotal in influencing knowledge transfer within organisations. According to Bandura [40] self-efficacy refers to an individual's belief in their ability to execute behaviours necessary to produce specific performance attainments. It significantly impacts the motivation and behaviour of professionals in complex and collaborative environments like those found in AEC projects [41]. Rios-Ballesteros and Fuerst [42] and Owusu-Manu et al. [43] underscored its significance for fostering individual and organisational learning, which in turn enables knowledge transfer processes within construction organisations [44]. In the context of the current study, knowledge gained in the use of digital technologies within AEC organisations can be transferred when individuals judge their capabilities to execute actions required for knowledge transfer amongst colleagues. Wang, Noe, and Wang [17] note that self-efficacy not only enhances the willingness of individuals to participate in knowledge-sharing activities but also increases their ability to absorb and apply new knowledge in the AEC field, especially where the successful implementation of projects often relies on the collaborative efforts of diverse professionals and the effective use of digital technologies. Thus, high self-efficacy can enhance confidence in implementing new technologies, methodologies, and processes, thereby facilitating a more robust knowledge transfer process. The literature supports the notion that self-efficacy is a foundational element that can influence knowledge transfer in construction organisations, aligning with the theoretical basis of the technology acceptance model (TAM) and emphasising the importance of individual factors in influencing knowledge transfer and innovation. Therefore, the study hypothesises the following:

H1: *DT self-efficacy will directly and positively influence DT knowledge transfer.*

H8: *DT self-efficacy will positively influence DT knowledge transfer indirectly through transfer motivation.*

2.3. Perceived Ease of Use (PEU)

Perceived ease of use is another core dimension of the TAM introduced by Davis [14]. It is referred to as the degree to which an individual believes that using a particular system would be free of effort [14] and would influence the decisions to use information technology [45]. In AEC organisations where the adoption of new digital technologies is evolving, the perceived ease of use of these innovations can significantly influence the effectiveness of knowledge transfer among practitioners. Jasimuddin and Almuraqab [46] emphasise its influence on the acceptance of digital technologies, aligning with the importance of technology acceptance in facilitating knowledge transfer. The perceived ease of use is a statistically significant predictor for end-user satisfaction, which demonstrates its influence on user attitudes and behaviours [47]. Furthermore, Suksa-Ngiam and Chaiyasoonthorn [29] and Nguyen and Fry [30] underscore the impact of the perceived ease of use on the adoption and capability for online knowledge-sharing. In AEC environments, characterised by high complexity and tight schedules, digital tools that are user-friendly and straightforward are more likely to be embraced by the workforce because they reduce cognitive load and are easier to assimilate when applying new information [48]. According to Lee et al. [49], the integration of easy-to-use digital technologies facilitates smoother communication and collaboration among team members and diverse stakeholders, which in turn enhances the efficiency and effectiveness of knowledge transfer. Overall, the literature supports the significance of perceived ease of use in influencing knowledge-sharing and transfer within AEC organisations. These arguments necessitate the following hypotheses:

H2: *Perceived ease of use will directly and positively influence DT knowledge transfer.*

H9: *Perceived ease of use will positively influence DT knowledge transfer indirectly through transfer motivation.*

2.4. Mastery Goal Orientation (MGO)

Mastery goal orientation, a concept rooted in achievement goal theory, emphasises learning, understanding, and competence development as primary objectives [35]. This orientation contrasts with performance goal orientation, where the focus is on demonstrating competence relative to others [50]. According to VandeWalle [51], individuals with a mastery orientation are more open to sharing their knowledge and learning from others, viewing these as opportunities for mutual growth rather than competition. Mastery goal orientation has also been linked to pre-training motivation and training self-efficacy, both of which are related to skill transfer [31,32]. Furthermore, Kubsch et al. [52] established a connection between mastery goal orientation and the organisation of knowledge networks and acquiring and developing competence [34], which collectively demonstrates its role in knowledge transfer. In the context of AEC organisations, mastery goal orientation plays a significant role in fostering knowledge transfer and collaborative learning environments (especially in achieving learning outcomes) [33]. It supports a culture of innovation and experimentation, allowing individuals to explore new methods, technologies, and processes without the fear of failure. Gong, Huang, and Farh [53] posit that these support organisational learning and knowledge transfer within the collaborative and interdisciplinary nature of AEC projects, where the integration of diverse knowledge and expertise is key to project success. These arguments collectively suggest that mastery goal orientation is significant in influencing motivation, learning, skill transfer, and knowledge organisation. Thus, we hypothesise in this study the following:

H3: *Mastery goal orientation will directly and positively influence DT knowledge transfer.*

H10: *Mastery goal orientation will positively influence DT knowledge transfer indirectly through transfer motivation.*

2.5. Supervisory Support (SS)

Supervisory support is a significant dimension in technology acceptance [54], as it influences subordinates' work environments through the nature of tasks that they perform and their interrelationships with organisational requirements [55]. Ho et al. [56] highlight supportive leadership in navigating the complexities associated with digital tools and enhancing knowledge-sharing practises. Also, Chiaburu et al. [57] assert its significance within AEC organisations as a critical predictor of training transfer in digital technologies. Active supervisory support helps in creating an environment conducive to learning, clearer intentions, and the actualisation of the application of new knowledge [58].

To maintain competitiveness and innovation, AEC organisations must prioritise and cultivate supervisory support as a core component of their knowledge transfer strategies to harness the full potential of digital technologies. Tacit knowledge, for example, is a challenging one to transfer and share within construction supply chains [36], as it requires an environment where employees feel supported to share their implicit understandings. Supervisors must actively support knowledge-sharing initiatives (and bridge the gap between diverse project disciplines and teams) so that critical knowledge is effectively communicated and applied [59]. According to Argote and Ingram [60], organisational knowledge bases can be greatly enhanced when supervisors promote a culture of experimentation and learning from mistakes. This approach fosters a safe and supportive environment for employees to share their successes and failures. In the AEC sector, projects are complex and multidisciplinary. Therefore, supervisors play a significant role in increasing the effectiveness of training and levels of knowledge transfer. In this study, the alignment of supervisory support with digital technology knowledge transfer initiatives is explored with the following hypotheses:

H4: *Supervisory support will directly and positively influence DT knowledge transfer.*

H11: *Supervisory support will positively influence DT knowledge transfer indirectly through transfer motivation.*

2.6. Peer Support (PS)

Peer support, which is characterised by assistance and encouragement among colleagues at similar hierarchical levels, plays a vital role in facilitating knowledge transfer and transformations [61]. This form of support is crucial in environments that are inherently collaborative and multidisciplinary, such as those found in AEC projects, where the sharing of expertise and experiences can significantly enhance project outcomes and innovation [62]. The literature on organisational behaviour highlights the importance of peer support in creating a conducive environment for knowledge exchange. It has been shown to foster a sense of belonging and mutual respect among team members, which in turn encourages them to share their knowledge more freely and openly [63]. Chiu et al. [64] link peer support to increased job satisfaction and reduced turnover intentions, which are critical for maintaining continuity and retaining tacit knowledge within organisations. Also, Reagans and McEvily [65] found that peer support enhances the absorptive capacity of teams, enabling them to integrate and apply new knowledge more effectively. In simulating experience transfer within the AEC industry, Lê and Law [66] provide insights into the dynamics of knowledge transfer for improving knowledge transfer and learning. Thus, peer support can mitigate the challenges posed by the complex and often siloed nature of projects, enabling more efficient and effective communication and collaboration across different disciplines [41]. Informal learning opportunities could be facilitated by peer interactions in environments where continuous professional growth is valued and supported [67]. Empirical studies within the AEC sectors have underscored the positive impact of peer support on the success of knowledge transfer [62]. In this study context, the relationship between peer support and knowledge transfer with transfer motivation as a mediating variable is investigated through the following hypotheses:

H5: *Peer support will directly and positively influence DT knowledge transfer.*

H12: *Peer support will positively influence DT knowledge transfer indirectly through transfer motivation.*

2.7. DT Usage (DTU)

The integration and transfer of digital technology knowledge in the AEC sector could significantly influence its capacity for innovation, efficiency, and a competitive edge. The evolving landscape of digital technologies underscores the need for effective knowledge transfer mechanisms. For example, building information modelling (BIM), could be a tool for innovation and efficiency in the AEC sector [10]. Also, cloud-based technologies and mobile applications in the AEC sectors have enabled real-time data sharing and accessibility, breaking down geographical and temporal barriers to knowledge transfer [68]. Minbaeva et al. [69] highlight the importance of subsidiary absorptive capacity and human resource management in facilitating knowledge transfer within multinational corporations, a concept that can be extended to the AEC sector to address the challenges of transferring digital technology knowledge across diverse organisational structures.

Moshood et al. [70] propose an integrated paradigm for managing efficient knowledge transfer, emphasising a comprehensive philosophy that holds benefits for the construction industry. This approach aligns with the necessity for AEC organisations to adopt holistic strategies that foster an environment conducive to the sharing and application of digital technology knowledge. Rotimi et al. [71], focusing on BIM knowledge transfer, suggest that a strategic analysis can enhance the sharing of specialised knowledge among practitioners, which is vital for the sector's advancement.

Yap and Toh [25] and Owusu-Manu et al. [43] investigate the factors and enablers of knowledge management and transfer within construction organisations. Also, Venkatesh et al. [48] offer a theoretical framework for understanding the user acceptance of information technology, which can be applied to study how AEC professionals adopt and adapt to new digital tools and processes. Identifying these elements is crucial for developing targeted strategies that overcome barriers to digital technology knowledge-sharing. Exploring technology-enhanced learning in the AEC sector, Wu, Luo, and Chan [68] present systematic evidence of the benefits and challenges associated with digital technology education and training. Ensuring that technology usage is perceived as useful and easy to use can significantly influence its adoption and the effectiveness of knowledge transfer within AEC organisations. In conclusion, the successful transfer of digital technology knowledge in the AEC sector is influenced by a combination of factors including absorptive capacity, integrated knowledge transfer paradigms, and the identification of key enablers and barriers. By focusing on these areas, AEC organisations can enhance their strategies for digital technology adoption, leading to improved innovation and competitiveness. Therefore, this study proposes the following hypotheses:

H6: *DT usage will directly and positively influence DT knowledge transfer.*

H13: *DT usage will positively influence DT knowledge transfer indirectly through transfer motivation.*

2.8. Transfer Motivation (TM)

Transfer motivation refers to individuals' desire to apply acquired knowledge in different contexts [72,73], thus bridging the gap between the acquisition of knowledge and their application. Noe and Schmitt [74] posit that individuals' motivation affects their willingness to share knowledge and their propensity to apply what they've learned to solving problems or improving organisational processes. Turner and Petrunin [75] and Lin [76] suggest that transfer motivation is intrinsic, such as altruism and absorptive capacity [77]; thus, individuals not only seek knowledge but are willing to contribute knowledge when motivated. Research has shown that several factors contribute to enhancing transfer motivation among professionals in the AEC sector. These include the perceived relevance of the knowledge to current projects or challenges, the recognition and rewards associated with the sharing of knowledge, and the support of supervisors and peers [60,78,79]. Also, organisational culture that values learning, knowledge exchange [80], reciprocity, and company cultural identity [81] can foster a climate where transfer motivation is heightened, facilitating a more robust knowledge transfer process.

Minbaeva et al. [69] stress the importance of individual employees' motivations to engage in knowledge absorption and transfer. Similarly, Na-Nan and Sanamthong [82] demonstrated the mediating effects of workplace support, transfer motivation, and transfer of training on the relationship between the self-efficacy and job performance of engineering alumni. In essence, transfer motivation could act as a mediator in the knowledge transfer process, influencing the extent to which knowledge is effectively applied. This is a microlevel (individual) consideration, as knowledge fundamentally resides in people and they may choose to share it or not [81]. In the context of the current study, digital technology end-users' motivation is explored to provide an understanding of how this can lead to more efficient knowledge-sharing and application within AEC organisations. Its significance as a mediating effect on the digital knowledge transfer process is hypothesised as follows:

H7: *Transfer motivation will positively influence knowledge transfer and sharing within work environments.*

3. Methodology

3.1. Survey and Sample

In this study, the target population comprised construction practitioners who had undergone training on the application of digital technologies, such as BIM, AR, VR, CostX, and Primavera, within their respective organisations in New Zealand. The researchers employed a chain referral or network sampling approach to recruit participants from their social networks [83]. This is a specific purposeful sampling technique widely known as snowball sampling, applied where the population is hidden or hard to reach [84]. Although random sampling is excellent for quantitative studies, the chain referral method provides a reasonably good solution by selecting participants who are initially unknown but knowledgeable about the area of study. Therefore, it reduces the sampling bias and ensures the robustness of findings. Utilising a Qualtrics survey, links were provided to individuals within the researchers' close networks, who in turn were encouraged to extend the survey links to others within their professional circles. The selection criteria for participation in the study focused on construction individuals who had received on-the-job training in digital technologies and were expected to apply their acquired skillsets to their work environments, including training work colleagues. As per this criterion, the population is mostly hidden to the researcher and thus, applying a random sampling technique is impossible. The selected sampling technique aimed to leverage existing professional networks to enhance their reach and the diversity of the study participants, ensuring a comprehensive representation of construction practitioners with relevant digital technology training and knowledge transfer experiences [85]. This representative and non-biassed method of sample selection ensures the robustness of the findings. Finally, 85 cases were collected satisfying the sample size requirement for PLS-SEM (partial least square structural equation modelling) analysis under the 10 times rule, wherein the sample size should be at least 10 times the largest number of structural paths directed to a particular latent construct [86]. Further justifications for selecting the PLS-SEM method for this study are provided under the data analysis subsection below.

The first section of the survey comprised seven questions on demographic factors, namely age, gender, education, construction job sector, country, and the BIM knowledge of the respondents. The second section included nine sets of seven-point Likert scale questions on the eight main model constructs (digital technology self-efficacy, perceived ease of use, mastery goal orientation, supervisory support, peer support, and digital technology usage), each containing six items, and the general opinion of participants about the usefulness of digital technologies, which contained seven items (refer to Appendix A).

3.2. Data Analysis

SPSS v21.0 software was used to calculate the frequencies and descriptive statistics related to the demographic variables (refer to Appendix A). The hypotheses concerning the effect of six knowledge transfer enablers (digital technology self-efficacy (DTSE), perceived ease of use (PEU), mastery goal orientation (MGO), supervisory support (SS), peer support (PS), digital technology usage (DTU)) and the mediating role of transfer motivation were tested using partial least square structural equation modelling (PLS-SEM). A structural equation modelling method was required in this study, as there are direct and indirect paths to be tested using the data collected on multi-item (latent) constructs (Appendix A). Since PLS-SEM is a non-parametric structural equation modelling technique, which is free from distributional assumptions and flexible for small sample sizes [83], it was selected as the best method of data analysis in this study that utilises a sample size of 85 and includes several non-normal variables indicated by the variables with skewness coefficients that are not within the range of -1 and +1 (Appendix A). In contrast to PLS-SEM, covariance-based structural equation modelling (CB-SEM) requires the data to be normally distributed and have larger sample sizes. Although it provides more robust estimates of path coefficients, PLS-SEM provides a good approximation of CB-SEM results even without the distributional assumptions and large samples [83].

SmartPLS 4 software was used to run the path model and the bootstrapping analysis. As explained in the Theoretical Framework and Model Development section above, the direct and indirect relationships between technology transfer enablers and actual digital technology transfer and the intermediary role of transfer motivation were supported by TAM (TAM 2), which provides an appropriate theoretical foundation based on the related enablers, intention to use, and actual system use [14].

3.3. Evaluation of the Measurement Instruments

The validity and reliability of the measurement instrument were tested using the relevant evaluation criteria provided by the PLS-SEM calculation. Composite reliability (CR) and Cronbach's alpha values were calculated for evaluating the internal consistency reliability of the measurement models, and the results were satisfactory. However, four items (DTU1, MGO1, PEU2, PS2) indicated a high risk of multicollinearity by large VIF values (greater than 5) and hence were deleted (Appendix A). The results of the finalised models are provided in Tables 1 and 2. According to the results in Table 1, the CR and Cronbach's alpha values of all the eight constructs were above 0.7, the minimum threshold. Hence, internal consistency was established for the modified measurement models. The AVE and CR measures were considered for the convergent validity assessment. The CR values were already satisfactory, and all the AVE values were greater than the minimum recommended value of 0.5. Therefore, convergent validity of the measurement model of each construct was adequately confirmed. In assessing the discriminant validity of the constructs, the HTMT ratio was used based on its higher quality relative to the alternative criteria [85]. All the HTMT ratios of the measurement variables shown in Table 2 were below the recommended maximum of 0.9 [85], indicating a satisfactory level of discriminant validity.

Table 1. Convergent validity and reliability.

Construct	Cronbach's Alpha	Composite Reliability	AVE
DTSE	0.897	0.919	0.655
DTU	0.898	0.925	0.713
DTKT	0.922	0.939	0.721
MGO	0.916	0.937	0.749
PEU	0.892	0.919	0.694
PS	0.931	0.947	0.781
SS	0.926	0.941	0.728
TM	0.910	0.930	0.689

Table 2. Discriminant validity (HTMT ratios).

	DTSE	DTU	DTKT	MGO	PEU	PS	SS
DTSE							
DTU	0.313						
DTKT	0.640	0.213					
MGO	0.168	0.532	0.224				
PEU	0.701	0.314	0.482	0.194			
PS	0.427	0.269	0.386	0.210	0.674		
SS	0.410	0.242	0.482	0.286	0.456	0.575	
TM	0.310	0.721	0.416	0.727	0.331	0.371	0.403

4. Results and Discussion

The reliability of the data has been established through the participation of suitably qualified professionals for the survey. The composition of the sample (Table 3) was studied based on six demographic factors, namely BIM knowledge, age, gender, education, and sub-sector in the construction industry. There were varied responses to the demographic questions. From the responses received, 60% of these consisted of construction employees whose DT knowledge involves the knowledge of BIM. More than half of the sample (53%) comprised construction employees aged between 25 and 44 years. Most of the selected participants were males. In total, 55 out of 85 employees were graduates, whereas most of them (37) had a postgraduate qualification as well. The sample comprised almost all the sub-sectors in the construction industry, including quantity surveying, project management, consultancy, structural engineering, construction (buildings), and architecture, respectively. According to its characteristics, the sample is fair and representative, which ensures a high degree of reliability of the responses.

Table 3. Sample profile.

Demographic Factor	Group	Frequency (%)
BIM knowledge	DT knowledge involving BIM	51 (60%)
	DT knowledge not involving BIM	33 (38.8)
Age	18–24 25–34 35–44 45–54 55–64z	6 (7.1%) 27 (31.8%) 18 (21.2%) 7 (8.2%) 2 (2.4%)
Gender	Female Male Prefer not to say	12 (14.1%) 46 (54.1%) 2 (2.4%)
Education	Certificate/diploma Degree Postgraduate	5 (5.9%) 18 (21.2%) 37 (43.5%)
Construction sub-sector	Architecture Construction (buildings) Construction (roads) Construction IT consultant/specialist Engineering (civil/structures) Engineering (MEP) Other Project management Quantity surveying	2 (2.4%) 7 (8.2%) 3 (3.5%) 7 (8.2%) 7 (8.2%) 1 (1.2%) 6 (7.1%) 12 (14.1%) 15 (17.6%)

Testing of Hypotheses

This study investigates six knowledge transfer enablers, digital technology self-efficacy (DTSE), perceived ease of use (PEU), mastery goal orientation (MGO), supervisory support (SS), peer support (PS), and digital technology usage (DTU). First, these six factors are assumed to have direct positive influence on digital technology knowledge transfer (DTKT) (H1–H6). Second, TM was theorised to have a direct positive influence on DTKT (H7) and be a mediator for the relationship between the six enablers and DTKT (H8–H13). Mediator analysis is a two-step process including the testing of models with and without the mediator. Therefore, initially, the PLS model with only the direct effects of six knowledge transfer enablers and DT knowledge transfer was tested by running a bootstrapping algorithm for 5000 samples. In this model, only the effects of DTSE (path = 0.534, p-value = 0.000) and SS (path = 0.213, p-value = 0.073) were significant (Table 4). Then, the full path model, including the mediator variable, was tested, and this enabled the testing of both direct and indirect effects of technology transfer enablers on DT knowledge transfer. In addition, the second model facilitated the investigation of the direct effect of technology transfer enablers on transfer motivation, the mediator variable. Figure 2 shows the final empirical model including all the direct and indirect effects of interest. Table 4 presents the results of both models fitted during the mediator analysis, including all the path coefficients and p-values.

Table 4. Results of hypothesis tests.

Direct Effect	Path Coefficient (Initial Model Excluding the Mediator)	Path Coefficient (Final Model with the Mediator)	Direct/Indirect Effects	Path Coefficient (Final Model with the Mediator)	Type of Mediation	Result
DTSE→DTKT	0.534 ***	0.515 ***	DTSE→TM DTSE→TM→DTKT	0.099 0.028	No mediation	H1 confirmed. H8 not confirmed.
PEU→DTKT	0.017	0.020	PEU→TM PEU→TM→DTKT	−0.075 −0.022	No mediation	H2 not confirmed. H9 not confirmed.
MGO→DTKT	0.115	−0.041	MGO→TM MGO→TM→DTKT	0.427 *** 0.123 *	Full mediation	H3 not confirmed. H10 confirmed.
SS→DTKT	0.213 *	0.197 *	SS→TM SS→TM→DTKT	0.107 * 0.031	No mediation	H4 confirmed. H11 not confirmed.
PS→DTKT	0.011	-0.020	PS→TM PS→TM→DTKT	0.120 0.035	No mediation	H5 not confirmed. H12 not confirmed.
DTU→DTKT	−0.034	−0.165	DTU→TM DTU→TM→DTKT	0.393 *** 0.113 **	Full mediation	H6 not confirmed. H13 confirmed.
			TM→DTKT	0.287 **		H7 confirmed.

Note(s): * significant at 10%; ** significant at 5%; *** significant at 1%.

It can be observed from the tests results in Table 4 that the study supports hypotheses H1 and H4, respectively, and identifies DT self-efficacy (path = 0.515, p-value = 0.000) and supervisory support (path = 0.197, p-value = 0.088) as the only factors that have a significant direct influence on DT knowledge transfer, although the influence of DTSE is larger. This finding aligns with Bandura and Wood's [87] position on the significance of self-efficacy in knowledge transfer performance. They suggest that the enhancement of self-efficacy is critical for individuals to develop a greater sense of confidence in their own abilities and to manage future outcomes [88]. Other studies present contrasting perspectives of self-efficacy in knowledge transfer [58]. For example, Chuang et al. [89] suggest that self-efficacy enhances the motivation to learn and to achieve better training performance. Similarly, Axtell et al. [90] did not find a direct link between self-efficacy and transfer but rather with training motivation. However, they add that self-efficacy may influence transfer via motivation. It has been suggested that the influence of self-efficacy varies across different domains [91]. In the context of the current study, self-efficacy was significant in DT knowledge transfer outcomes within the AEC sector.

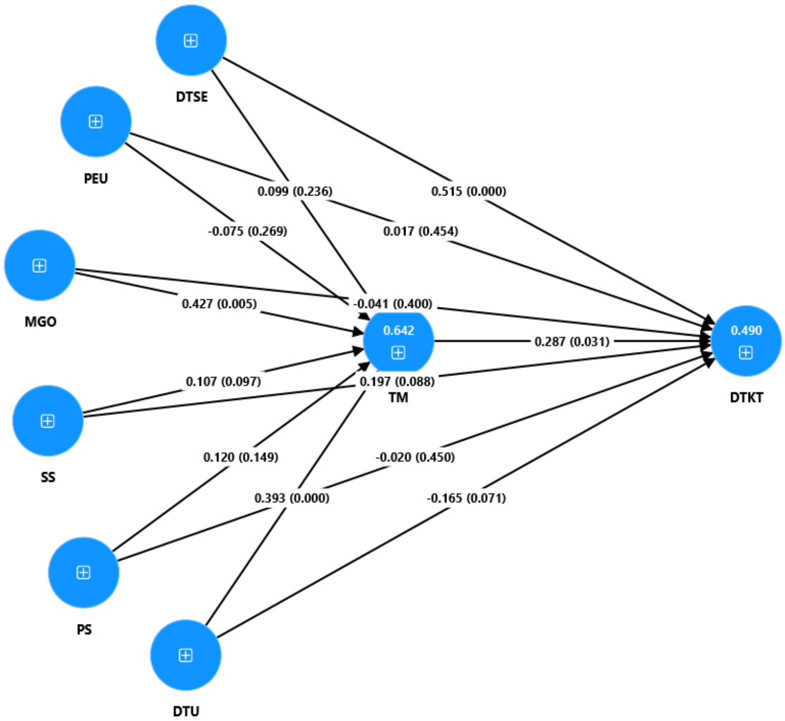

Figure 2. Path model.

Although the study finds that supervisor support has a marginally significant positive influence on the transfer of DT knowledge in AEC organisations, it is worthy of consideration within the context of this study investigation. Most importantly, supervisory support also has a marginally significant positive influence (path = 0.107, p-value = 0.097) on transfer motivation, although its indirect effect on DT knowledge transfer is not statistically significant. The support of a supervisor is important for technically competent workers to share their knowledge with peers. The literature confirms that supervisor support leads to increased knowledge-sharing behaviours [92], especially where there is a high level of affective organisation commitment [93]. As alluded to earlier, supportive leadership plays a crucial role in successfully navigating the challenges associated with the use of digital tools and fostering a culture of knowledge-sharing within AEC organisations [56,57]. Having active supervisory support is crucial in fostering an atmosphere that is conducive to learning, which in turn leads to a higher level of intention and the successful implementation of new knowledge. When supervisors are fully engaged in supporting their team members, it creates a positive and encouraging learning culture that inspires individuals to apply their newfound skills and knowledge with confidence [58]. In the AEC sector, digital technology knowledge-sharing is an important process that requires significant time and effort considering that technology adoption is largely impeded by a lack of systematic frameworks [94]. In such cases, having supervisory support becomes crucial, as it can greatly facilitate and ensure the success of knowledge transfer processes. The supervisor's cooperation, guidance, and facilitation can help employees overcome any challenges they might encounter and enable them to share their knowledge effectively. Therefore, within the context of digital technology knowledge-sharing in the AEC industry, supervisory support is not only justifiable but also highly beneficial. However, since the indirect effect of supervisory support through motivation is not significant as expected, managers would need to identify more effective means to increase the motivation of employees because it will ensure a more sustainable transfer of digital technology knowledge. Introducing systematic knowledge-sharing sessions rather than informal team-based work environments is a possible reason for the observation.

Additionally, the study data reveal a significant direct effect of several DT transfer enablers on transfer motivation (Table 4). In particular, mastery goal orientation MGO (path = 0.427, p-value = 0.005) and digital technology usage DTU (path = 0.393, p-value = 0.000) were found to be the major factors affecting motivation to transfer knowledge in digital technologies. Therefore, MGO and DTU are identified as the enablers that significantly improve transfer motivation, which in turn increase the actual transfer of DT knowledge. These findings support Chiaburu and Marinova's [32] study on the predictors of skills transfer, wherein pre-training motivation is closely related to MGO. Thus, encouraging construction workers to cultivate MGO while actively employing their knowledge in DT could enhance their motivation to transfer knowledge to others. Although Swift et al. [95] have shown that organisations may need to acknowledge different goal orientations and how they promote effective knowledge-sharing practises, individual goals and personal traits/characteristics [96] influence the perceptions of benefits to be gained from knowledge-sharing [97]. In other words, workers in the AEC sector who embrace the opportunity to learn new and challenging skills necessary for effective job performance may be more inspired to share their knowledge of DT practises with others in the workplace, especially when DT training is integrated into their daily work routines.

This study does not confirm the hypotheses related to perceived ease of use (PEU) (H1 and H9) and peer support (PS) (H5 and H12). Both factors do not have statistically significant effects on either DT knowledge transfer or transfer motivation. Tech-savvy staff in today's companies may be a reason that ease of use is not a contributing factor for DT knowledge transfer. Recent research with similar findings [98] highlights the importance of promoting peer engagement and support, which might be lacking in post-pandemic virtual work environments.

Finally, the results in Table 4 show that H7 asserts a positive relationship between transfer motivation TM and DT knowledge transfer. This is significant at a 5% level (path = 0.287, p-value = 0.031). This implies that the motivation of employees is an essential driver for the transfer of digital technology knowledge within AEC organisations. Furthermore, the statistical results reveal that transfer motivation fully mediates the effect of mastery goal orientation (path = 0.123, p-value = 0.066) and DT usage (path = 0.113, p-value = 0.029) on knowledge transfer and hence, the hypotheses H10 and H13 are supported. In simpler terms, employee motivation to transfer knowledge is a key factor that determines the success of knowledge transfer initiatives within AEC organisations. Also, transfer motivation fully mediates the influence of mastery goal orientation and digital technology usage on knowledge transfer. These findings align with previous research on the significance of motivation in increasing the propensity for organisation members to engage in knowledge-sharing activities that could facilitate knowledge transfer within their organisations [44,60,78]. This underscores the need for construction organisations to prioritise the implementation of strategies that promote knowledge-sharing cultures [98]. By focusing on employee-supportive practises (supervisory support/effective leadership, mentoring, training, etc.), employees could gain a deeper understanding of digital technologies and their applications in the construction industry. Also, conducive work environments and organisational culture that value learning and knowledge exchange can foster a culture that promotes transfer motivation among employees [80,81]. Creating a positive transfer environment requires sustained efforts and long-term commitment from organisations [99]. In summary, prioritising employee motivation to transfer knowledge is a critical component of building a successful knowledge-sharing culture within organisations. By investing in training and development, incentivising knowledge transfer, and promoting collaboration, organisations can drive innovation, increase productivity, and achieve their digital technology adoption goals more effectively.

5. Conclusions and Recommendations

This study is theoretically grounded in the technology acceptance model (TAM), and it analysed the key factors that facilitate efficient knowledge transfer among end-users of digital technologies in the AEC industry. The key factors include ease of use, perceived usefulness, training and support, self-efficacy, and mastery goal orientation. By examining the mediating role of transfer motivation, the study sheds light on the relationship between these enablers and knowledge transfer effectiveness. The intent is to enhance the understanding of how digital technology knowledge could be harnessed more effectively within AEC organisations. This ultimately contributes to capacity building initiatives that are required to facilitate the adoption of new technologies within AEC organisations. Thus, the study findings have both theoretical and managerial implications, as outlined below.

5.1. Theoretical Implications

The study contributes to the growing literature on digital technology adoption within the AEC sectors [1,2,8,11,71]. While most conceptual work on knowledge transfer has focused on specific DT tools, e.g., [4,7,21], AEC sub-sectors, e.g., [5], and the challenges and enablers of DT of AEC practises like sustainability [3] and innovation [13], the current study takes the DT training and knowledge transfer perspective. This approach has provided theoretical justifications for the significance of mastery goal orientation digital technology usage as major factors affecting the motivation to transfer knowledge in DTs within the AEC sectors. The study also found that supervisory support, while showing a marginal significance, does have a positive influence on individuals' motivation to transfer knowledge acquired from digital technologies within organisations. In addition, the study highlights the importance of considering other forms of supervisory support, such as encouraging and facilitating in-house peer-support workshops, which could potentially increase employee motivation to transfer DT skills to others.

Furthermore, the study illustrates the mediating role of transfer motivation as it fully mediates the effect of mastery goal orientation and DT usage on knowledge transfer. Considering the measures of mastery goal orientation used in this study, therefore, challenging working environments encourage employees to transfer DT knowledge. Also, when employees are provided more opportunities to apply their digital skill training outcomes to real projects, their motivation to transfer their DT skills to their peers intensifies. Given the pivotal role of transfer motivation as a driver for transferring the knowledge of digital technology within AEC organisations, managers must prioritise factors that contribute to transfer motivation, including fostering collaborative team environments.

The study finds that DT self-efficacy is the most significant driver of knowledge transfer. This is an important construct, as the literature suggests that DT self-efficacy has an even greater role in the construction industry's digital transformation as a key driver of DT adoption [93]. While it is possible to transfer DT skills amongst employees through various means, merely transferring knowledge may not necessarily boost employees' DT confidence. Therefore, supervisors must pay attention to this, as it could truly lead to enhanced employee confidence in DT. In addition to real world applications, opportunities to transfer DT skills to peers may have a backward positive effect on DT self-efficacy too.

The TAM has several applications in construction industry research, where IT adoption has been investigated [100–103]. Along with these studies, the current study contributes to the theory by extending the TAM application to AEC sectors. Most importantly, it addresses the theoretical gap highlighted by Davis (1993) [104] to explore additional variables within the TAM other than attitude and perceived ease of use that could motivate users of technologies. While incorporating the attitude and the system use in the TAM in terms of motivation and DT knowledge transfer, this study conceptualises and empirically tests additional variables such as supervisory support, peer support, etc., in a digital technology adoption context within AEC sectors.

5.2. Managerial and Practical Implications

In the evolving landscape of the construction industry, the significance of DTKT stands firm. The sector faces mounting pressure for digitalization, urging a pivotal focus on enhancing productivity. As younger tech-savvy professionals ascend to leadership roles and enter the workforce, the retention of decades-old practical wisdom from seasoned experts becomes invaluable for sustained industry progress. The convergence of fresh perspectives with seasoned experience underscores the critical need for seamless intergenerational knowledge transfer within and beyond DT. Therefore, embracing these direct determinants of DTKT (DTSE and SS) is paramount for propelling the sector forward with resilience and adaptability.

Reflecting on the measures of DTSE, strategies like structured graduate programmes in the industry and work-integrated learning facilitated by universities may stand out as key catalysts. These initiatives empower tech-savvy professionals to apply their digital transformation skills in real-world problem-solving scenarios, collaborating with seasoned experts. By engaging in such programmes, graduates can enhance their confidence in digital transformation, leading to a direct positive influence on DTKT. The study incorporated various sources of learning to measure DTSE. The participants were positive that user confidence increases when someone introduces a new technology to them. Supervisors play a crucial role by motivating younger generations and allocating dedicated time to showcase the benefits of DT to older employees. This approach enhances DT confidence in senior employees, enabling them to transfer skills to their colleagues.

Supervisors may play a crucial role in promoting tech-savvy professionals as 'experts' within their teams. This research indicates that peer support does not directly impact DTKT. Interestingly, participants showed a positive response towards self-efficacy when guided by another individual on DT usage. The distinction suggests that employees value peer support when they view the peer as a DT expert. This insight highlights a potential direction for future research exploration.

While formal DT training programmes are beneficial, the research also suggests that informal methods, like freely available online resources, positively impact self-efficacy. Thus, organisations can support employees by offering subscriptions to platforms like LinkedIn Learning for enhancing DT skills. Despite a minor direct influence on DTKT by SS, the industry should not underestimate the significant contribution of supervisors in boosting DTSE among staff. Thus, viewing SS and DTSE holistically is key to crafting effective strategies for fostering a culture that promotes DTKT.

Furthermore, AEC managers will need to think beyond their traditional roles to facilitate digital technology adoption and innovation within their organisations. AEC managers will need to be more proactive by nurturing competencies and capabilities in line with those suggested by Adafin et al. [105]. The study's findings suggest that implementing tailored training programmes, shifting organisational culture, and encouraging collaboration among stakeholders are critical to the successful integration of DTs in the AEC sectors. These suggestions lend themselves to ongoing challenges in AEC organisations to adopt new technologies. For example, Almatari [106] indicated the absence of clear guidance for learning and capacity building within construction organisations. Thus, to promote knowledge transfer and capacity building initiatives, organisations should consider incentivising employees through recognition programmes, performance-based bonuses, or other means that motivate employees to share their knowledge and expertise with their peers. Making more interactive team-based work environments that ensure the natural or informal sharing of knowledge rather than arranging systematic knowledge-sharing sessions would help in improving the motivation of employees to transfer DT knowledge among peers in more sustainable ways. By creating environments encouraging knowledge-sharing and collaboration amongst stakeholders, organisations can foster a culture of innovation and continuous improvement, contributing to a more digitally adept construction industry.

5.3. Limitations and Future Research

The study has limitations that must be addressed in future research investigations. Caution is required when generalising the findings to different contexts and domains due to the limited sample size and geographical coverage in this study. The significant factors influencing DKST included DTSE, SS, MGO, and DTU. Their measures may be similarly interpreted by individuals in Australia given the comparable socio-economic environments. However, it is crucial to acknowledge potential cultural variations in interpretations in diverse contexts. Therefore, future studies must ensure that their samples are diverse and representative to ensure that the findings are applicable to the broader sector. Additionally, the study was based on modifications to the TAM, which has also been subject to subtle modifications in some other domain-specific studies. Since there are limited attempts to identify the DT knowledge transfer enablers within AEC sectors, further investigations, particularly into the factors that are found insignificant in this study, would be useful. Another limitation of this study is that it broadly considers various digital technologies used in AEC sectors. Therefore, future studies focusing on different technologies (BIM, VR, etc.) are required to reach specific findings related to these technologies and perform comparisons between the effects. To generate insights, future research should also capture the perceptions of AEC practitioners through in-depth interviews. In conclusion, this study recommends that these issues be addressed to improve the validity and applicability of future research findings.

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Appendix A. Operationalization of Model Constructs and Descriptive Statistics of Measurement Variables

Construct/Measurement Variable	Coding	Mean	St. Dev.	Skewness	Outer Loading
Digital Technology Usage (DTU)					
I use my DT training skills on the job intensively every day	DTU1 *	4.92	1.750	−0.693	-
I use DT training skills on the job frequently every day	DTU2	5.11	1.660	−0.86	0.850
I spend a lot of time using my DT skills on the job	DTU3	4.84	1.704	−0.576	0.909
My job performance is accomplished by the use of DT	DTU4	5.01	1.716	−0.774	0.856
I strongly recommend my organisation to use DT on our projects	DTU5	5.97	1.216	−1.826	0.752

Construct/Measurement Variable	Coding	Mean	St. Dev.	Skewness	Outer Loading
Our projects have been facilitated through the use of DT	DTU6	5.50	1.501	−1.286	0.848
Transfer Motivation (TM)					
I am very excited about using my DT knowledge at my workplace	TM1	5.63	1.381	−1.615	0.845
I intend to transfer DT training contents to the workplace	TM2	5.60	1.295	−1.467	0.844
The transfer of DT knowledge increases our ability to work	TM3	6.04	1.125	−2.030	0.820
DT knowledge transfer has increased the interactions among our team members	TM4	5.35	1.358	−1.117	0.806
I am encouraged by how my workplace has implemented DT	TM5	5.38	1.487	−1.253	0.802
The knowledge and expertise of my team has increased as a result of my DT knowledge	TM6	5.24	1.247	−0.986	0.861
Mastery Goal Orientation (MGO)					
The opportunity to learn new things is important to me	MGO1 *	6.48	1.026	−3.127	
The opportunity to do challenging work is important to me	MGO2	6.29	1.078	−2.885	0.915
In learning situations, I tend to set fairly challenging goals for myself.	MGO3	5.94	1.036	−1.760	0.867
I always challenge myself to learn new concepts	MGO4	6.12	1.089	−2.166	0.909
I often look for opportunities to develop new DT skills and knowledge	MGO5	5.71	1.423	−1.520	0.877
I try to avoid performing poorly in the tasks required for my job	MGO6	6.24	1.229	−2.278	0.750
Perceived Ease of Use (PEU)					
It is easy to do what I need to do with DT	PEU1	5.41	1.315	−0.902	0.773
Learning to use DT is clear and understandable	PEU2 *	5.24	1.254	−0.520	-
Interacting with DT is easy	PEU3	5.22	1.069	−0.299	0.836
It is easy to become skillful at using DT	PEU4	5.08	1.418	−0.250	0.853
It is easy to learn DT skills	PEU5	5.10	1.241	−0.186	0.859
DT is flexible to interact with	PEU6	5.27	1.208	−0.430	0.842
Supervisory Support (SS)					
My supervisor helps me when I ask for advice on how to use my DT skills	SS1	5.00	1.402	−0.187	0.823
My supervisor is tolerant of changes that I initiate as a result of my DT skills	SS2	5.15	1.424	−0.627	0.853
My supervisor offers the opportunities to use my DT skills in the work environment	SS3	5.41	1.371	−0.708	0.85
My supervisor rewards me for using my DT skills at the workplace	SS4	4.80	1.526	−0.151	0.839
My supervisor is good at providing guidance that could facilitate DT at my workplace	SS5	4.74	1.601	−0.235	0.898
My supervisor shows that they have confidence in my DT skills	SS6	5.20	1.470	−0.906	0.853
Peer Support (PS)					
My co-workers care about my application of DT skills in the work environment	PS1	5.46	1.77	−1.166	0.888
My co-workers encourage me to use DT skills in the work environment	PS2 *	5.48	1.260	−0.925	-
My relationship with my co-workers enables me to use DT training skills	PS3	5.39	1.201	−0.695	0.923

Construct/Measurement Variable	Coding	Mean	St. Dev.	Skewness	Outer Loading
My co-workers accept my mistakes as part of trying out DT skills in the work environment	PS4	5.34	1.094	−0.574	0.850
My co-workers allow me to get accustomed to using DT in the work environment	PS5	5.46	1.089	−0.212	0.891
My co-workers offer me constructive feedback on the use of my DT skills in the work environment	PS6	5.25	1.178	−0.309	0.866
Digital Technology Self Efficacy (DTSE)					
I am very confident in my abilities to use DT	DTSE1	5.59	1.070	−1.296	0.838
I am very confident in my abilities to use DT, even if I only have online instructions for reference	DTSE2	5.57	1.087	−1.322	0.867
I am confident to use DT if somebody shows me how to use it first	DTSE3	5.75	1.027	−1.008	0.709
I can usually deal with most difficulties I encounter when using DT	DTSE4	5.43	1.176	−0.963	0.854
I am good at using my DT knowledge on challenging tasks	DTSE5	5.49	1.247	−1.181	0.806
I am able to figure out how to help my organisation using my DT knowledge	DTSE6	5.48	1.134	−0.256	0.771
Digital Technology Knowledge Transfer (DTKT)					
I frequently participate in DT knowledge sharing activities	DTKT1	4.90	1.399	−0.726	0.815
I spend a good deal of time conducting DT knowledge sharing activities with my peers	DTKT2	4.57	1.586	−0.321	0.873
I usually actively share my DT knowledge with others	DTKT3	5.20	1.376	−0.883	0.906
I usually involve myself in discussions about various DT topics	DTKT4	4.95	1.554	−0.632	0.882
My co-workers are now comfortable using DT because of me	DTKT5	4.38	1.675	−0.582	0.804
I usually involve myself in solving complicated DT issues	DTKT6	4.85	1.436	−0.711	0.807

Note(s): * the item was deleted during the measurement model validation process.

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