

Article

Modelling the Determinant of Digitalization for Effective and Sustainable Construction Workforce Management in South Africa

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Abstract

Workforce management in the construction industry in developing countries like South Africa is still plagued by skills shortages, low productivity, and inadequate adoption of new technologies. This paper examines the factors influencing the adoption of digital technologies for sustainable construction workforce management in South Africa, using the Technology–Organization–Environment (TOE) model as the guiding theory. A quantitative research approach was adopted with data gathered from a questionnaire survey carried out on selected construction organizations, and the data were analyzed using covariance-based structural equation modelling (CB-SEM). It was found that both the technology dimensions comprising compatibility, competence, relative advantage and complexity, and the environmental dimensions including government policy, legislation, and competition significantly predicted the effective use of digital technologies in workforce management, while the organizational dimension failed to do so ($\beta = 0.10$). Also, effective digitalization was significantly associated with worker participation and productivity, rapid employee development, optimal reward and information management, as well as talent recruitment and retention.

Keywords: CB-SEM; construction workers; digital technologies; human resources; innovation; sustainable workforce management



Academic Editors: Baiba Rivza and Rosita Zvirgzdina

Received: 21 June 2026

Revised: 9 July 2026

Accepted: 10 July 2026

Published: 14 July 2026

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1. Introduction

As a labor-intensive industry, construction is a major employer in both developed and developing nations [1]. Over time, it has become imperative for construction organizations to effectively manage their workers to harness their full potential and achieve organizational goals [2]. The current fourth industrial revolution offers organizations the opportunity to transform their business models through emerging digital tools. Deploying these digital tools can also improve organizations' workforce management while ensuring growth in labor productivity [3,4]. For instance, by employing big data analytics and cloud computing, which are data-driven technologies, organizations can better understand the personalities and behavioral patterns of construction workers. This is particularly valuable during recruitment, training, performance evaluations, and compensation decisions [5]. Additionally, innovative technologies such as 3-Dimensional (3D) printing, robotics, and

drones offer safer methods for performing construction tasks, thereby enhancing occupational health and safety management among workers [6,7]. Smart wearables can also play a crucial role in monitoring the health and well-being of construction workers on-site [8], while cyber-physical systems, augmented reality (AR), and virtual reality (VR) provide valuable training resources for construction workers [9].

Unfortunately, despite growing interest in digital technologies, the construction industry has been slow to adopt these innovations, particularly in developing countries such as South Africa [10]. The slow adoption process is occurring amid ongoing workforce management issues, which make the construction industry in South Africa highly relevant and topical for this study. The construction industry in the country remains among the least productive, with labor productivity among the lowest in developing countries. The industry is also a low contributor to national GDP (2% of GDP) despite being labor-intensive [2,11]. At the same time, a paradoxical skills situation exists in the industry: there is no general shortage of workforce, but there is an obvious shortage of skilled and certified workers. This mismatch in the industry can be attributed to several factors, including a weak apprenticeship system, low pay rates, and high training costs [12,13]. Statistics on occupational health and safety in the country further demonstrate the severity of the problem. The construction industry is one of the most dangerous industries in South Africa, with 1.5 to 2 worker fatalities per week on average [14]. The most frequent causes of injury and compensation claims include falls from heights, being struck by objects, and electrocutions [15]. All in all, these pressures have contributed to poor performance and a lack of innovation among many construction companies, thereby negatively affecting the national workforce [12].

Although the literature on digital technology adoption in construction is growing and the Technology–Organization–Environment (TOE) framework is widely used as the theoretical lens for understanding determinants of technology adoption [4,16–18], an important gap remains. In particular, while existing TOE-based investigations in construction have mainly explored the antecedents of technology adoption by focusing on technological, organizational and environmental factors, the actual outcomes of the adoption on the workforce have been largely ignored. Such an unbalanced focus means there is currently no empirical evidence on whether and how the adoption of digital technology leads to improved management, development, compensation, and retention of workers in the construction sector in developing countries [12]. To the best of the authors' knowledge, no research has empirically investigated whether and how TOE-based antecedents of technology adoption could impact the sustainable management of the construction sector workforce driven by digital technology. It is a fundamental rather than a marginal gap because understanding the implications of digitalization is at least as important, if not even more so, than understanding its antecedents: organizations cannot justify their investments in digital technology without proving the benefits in terms of more effective management of the workforce. The gap is especially important for the case of South Africa because the current management of construction workers there has been paradoxical: although workers represent the core of the industry, very little attention has been paid to them and the potential of digital technology in addressing this issue has been largely unexplored [2,12].

In order to advance workforce management in the construction industry, this study identified the factors which affect the use of digital technologies in construction organizations using the TOE framework, which has been proven useful in technology adoption research. The study modelled the relationship between these TOE-based factors and the adoption of digital technologies for effective and sustainable construction workforce management in South Africa. This work bridges the gap in previous studies by combining the antecedents to adoption and the subsequent influence of adoption in sustainable con-

struction workforce management. The findings provide valuable empirical insights into how these technologies can promote construction workforce management. By understanding these potential relationship from empirical findings, organizations and their human resource management departments can leverage these insights to transform their service delivery and workforce management.

2. Digitalization and Construction Workforce Management Nexus

The global construction industry faces two general demands: using digitalization to improve its competitiveness and productivity, as well as achieving its sustainability goals of environmental, social, and economic dimensions. Workforce management is where both issues intersect because all construction projects require a labor force, and traditional labor management methods are inefficient, risky, and offer poor real-time monitoring capabilities [12,19]. The Fourth Industrial Revolution, characterized by cyber-physical systems, the Internet of Things (IoT), cloud technologies, and artificial intelligence (AI), among others, opens new possibilities for rethinking how construction workforces should be managed, monitored, coordinated, and developed [12,20]. Similarly, the concept of sustainable workforce management is no longer just about adhering to occupational health and safety regulations. It is considered a multifaceted and multidimensional construct in the contemporary literature that takes into account the economic, social, environmental, and personal aspects of people management [21]. Sustainable human resource management theory views workforce management as a strategic process that contributes to the environmental performance and social responsibility of the organization, and also to its long-term economic sustainability [20,22]. The synergistic effect of combining digital technology and sustainable workforce management provides efficiency, reduced environmental impact, worker safety, and worker development [23].

The economic sustainability dimension of workforce management relates to the organization's ability to ensure its productive and competent labor force in the long run. This involves proper compensation systems, incentive schemes, and the optimal distribution of human capital resources in order to ensure maximum output by the organization without harming workers [22,23]. Unfortunately, the economic sustainability of construction organizations is jeopardized by the ongoing problems of skill shortage and low productivity of the labor force of the industry that can be solved by applying digital technologies [12,18]. On the other hand, the social sustainability dimension addresses the organization's responsibility to its workers and the community at large. This involves the proper protection of workers' rights, equality and diversity in employment practices, workers' health and safety, and the creation of decent working conditions [21]. Social sustainability is especially important for South African construction organizations that are characterized by exploitation of workers, poor working conditions, and inequality issues [2]. Digitalization tools such as safety wearables, drones, and monitoring systems help to facilitate the social sustainability of organizations [12,20]. The environmental sustainability dimension implies that organizations should ensure their labor force in such a manner that does not harm the environment. This involves reducing the carbon footprint of labor operations, promoting sustainable commuting and construction-site activities, and using technologies that enable workforce monitoring and avoid unnecessary site visits. Environmental sustainability is especially vital in construction, one of the most damaging industries, whose projects contribute most to environmental degradation [12,18,19].

The digitalization of construction workforce management comprises a variety of technologies and platforms. The first technology to become a primary access point for construction workforces is mobile apps, which provide interfaces for time tracking, task assignment and reporting, safety management, and communication [4,24]. Studies show that

mobile apps can serve as a link between field operations and office management, especially for geographically dispersed projects, where they can speed up information exchange and decision-making [25]. Similarly, Human Capital Management Systems (HCMS) include platforms that integrate workforce planning, recruitment, training, performance assessment, and payroll management. The adoption of HCMS by construction organizations can lead to benefits such as shorter recruitment periods, increased interdepartmental coordination, and more efficient administrative procedures [26]. In the same vein, using cloud-based platforms, data is centrally stored and available to the various parties involved [27,28]. Cloud computing and big data-enabled human resource analytics allow performance data to be analyzed faster and more easily. Such data provide managers with the necessary information to understand and address problems related to poor employee behaviors and outcomes [29].

Analytics and artificial intelligence (AI) platforms analyze data from various sources to provide insights and predict outcomes. Predictive analysis can be used by contractors to minimize incident rates, while machine learning (ML) algorithms can help optimize scheduling, resource allocation, and quality control [22,30]. Using AI and data analytics platforms, organizations can analyze CVs, online profiles, and internal metrics to automate screening, identify high-potential employees, and reduce bias [31,32]. The primary use cases include talent sourcing, analytics, and candidate experience optimization [33]. Predictive candidate sourcing uses data analytics to identify high-potential candidates and the optimal sources for recruiting them [34]. With the help of smart algorithms, CVs and applications are analyzed, helping organizations rank candidates and drastically reduce time-to-hire. In addition, performance prediction leverages historical data to determine characteristics of successful hires and predict future job performance [34,35]. It has also been noted that AI-based analytics and online learning platforms, along with instant feedback systems and goal-setting applications, can improve efficiency, increase transparency, and facilitate agile and personalized learning. These technologies help employees engage more effectively, work in hybrid environments, and provide objective information for decision-making [36,37]. Using AI to analyze workforce helps identify top performers, predict turnover, and identify skills gaps to implement training programs [37,38]. Furthermore, VR/AR is useful for training, allowing workers to simulate dangerous situations and respond in a controlled environment where they will not be harmed. Robotics and drones are used to perform inspections in inaccessible areas and hazardous work environments, protecting workers from dangerous conditions [8,9,39,40].

Building Information Modelling (BIM) enables certain capabilities that could be beneficial for workforce management. It reduces blind spots in 2D drawings, enables collaboration with other stakeholders, improves resource coordination and quality control, and supports sound decision-making. Similarly, the 4D and 5D dimensions of BIM enhance scheduling and budgeting capabilities, improving coordination of workforce allocation [12]. According to Calvetti et al. [41], BIM integration helps increase coordination among project teams, resulting in reduced rework and delays and improved labor productivity and resource efficiency. Also, safety planning and prevention-through-design methods are among the most important features of BIM for workforce management. It allows the visualization of construction sequences and identification of potential hazards using the digital model, enabling the implementation of necessary interventions before workers are exposed to these hazards. Visualization of safety measures and analysis of dynamic hazards are possible with BIM models, which are especially useful for complex construction projects involving multiple trades working in confined spaces and at high altitudes [12,42]. Moreover, the integration of BIM improves labor forecasting and allocation. Scheduling tools based on BIM enable the simulation of different crew configurations, the identification of conflict-

ing resources, and the optimization of labor allocation and performance across multiple tasks [28]. It allows for reduced idling times and crew interference, and for higher labor productivity. The mentioned digital methodology allows for optimizing construction duration and cost through multifactor analysis and scenario forecasting with higher labor productivity and lower costs [28].

Digital twin technology is the most sophisticated combination of BIM, the IoT, and AI, resulting in dynamic models of construction sites that are regularly fed by real-time data [43,44]. With digital twins, it becomes possible to implement closed-loop control systems in which detected conditions trigger an automatic response or provide decision-support warnings, thereby making construction management a proactive process [44]. For workforce management, digital twins provide real-time information on worker locations, actions, safety status, and performance [43,45]. An IoT sensor network serves as the data source for digital twins. Physiological wearable sensors track parameters such as heart rate, body temperature, and fatigue level, allowing early detection of heat stroke or exhaustion [26]. The environmental sensors record temperature, humidity, air quality, and noise, ensuring that occupational health standards are met [43]. Similarly, location-tracking systems using Global Positioning System (GPS), Radio-Frequency Identification (RFID), or ultra-wideband technologies enable real-time data on the worker's position [30]. AI-based digital twin models that integrate IoT, BIM, and ML can be highly beneficial for environmental sustainability in smart construction. The benefits include predictive energy optimization, real-time carbon monitoring, and decision support for material selection, logistics, and waste reduction in the pursuit of net-zero targets. The AI-based digital twin models make the projects more resilient in the context of smart city construction and contribute to the research on digital transformation [43].

Evidently, the digitalization of construction worker management, coupled with sustainable workforce management practices and the leveraging of emerging digital technologies, presents a great opportunity for the construction industry. It is therefore important to understand the factors that could facilitate the seamless diffusion of digital technologies into construction practices to ensure effective worker management.

3. Determinants of Digitalization Deployment for Efficient Construction Workforce Management

The TOE Framework, developed by Tornatzky and Fleischer in the 90s, offers an excellent scientific foundation for exploring digital technology adoption within construction organizations. Unlike other individual-centered frameworks, such as the Technology Acceptance Model or Unified Theory of Acceptance and Use of Technology [46], which explain technology acceptance by the end-user, TOE works at the organizational level. This makes it theoretically feasible to explore organizational resource allocation, procurement, and policy decision-making issues directly related to the adoption of digital technologies for workforce management [47,48]. Through its division into three separate yet interrelated environments, the TOE framework provides a useful tool for academics and business managers to study how factors in both internal and external environments enable or constrain the diffusion of digital innovation [49–51]. Moreover, by incorporating technological, organizational, and environmental dimensions, TOE captures both internal capabilities and external forces in contrast to other frameworks, such as the Diffusion of Innovation theory, which are rather one-sided with the focus on technology itself. The multidimensionality of TOE allows for a more complete description of adoption decisions in project-based industries, such as construction, where technology adoption does not occur solely because of technological considerations. In practice, this theoretical construct is often applied using quantitative techniques to measure the strength and significance of these factors across various sectors

and industries, ranging from manufacturing, healthcare, e-business, maritime and banking to agriculture and construction [52–54]. This framework is especially appreciated for its ability to provide a comprehensive picture of the socio-technical factors behind technology adoption [49,50]. Being a meta-framework, the TOE can be easily adapted for different contexts due to operationalizing its constructs specifically for each situation. This provides an opportunity to justify the adaptation of the TOE framework for developing economies, such as South Africa, where organizational formality and governmental enforcement differ from those in the developed countries where TOE originated.

Technology—The focus on this dimension lies on the inherent features of the technology itself and the technological readiness of the organization internally [55,56]. Past studies have measured this dimension from the perspective of relative advantage, technology readiness, complexity, compatibility, availability and digital competencies and knowledge available within an organization [52–55]. Evidently, the successful use of digital technology requires a proper technological infrastructure comprising devices, applications, information, computers, software, and hardware [57]. Baker [47] explained that pre-existing technological capacity in an organization represents a basis for introducing new technology. In addition, it improves organizational readiness to introduce innovative technology. Also, technology competence, which refers to human knowledge of technology and its effects on the innovation process, is a crucial technological factor influencing technology use [58]. Metaxiotis [59] argued that technological competence is not only about available technology but also about people's creativity and skills, enabling organizations to remain competitive. According to Amoako et al. [60], a shortage of key technical skills among workers leads to difficulties in recognizing the benefits of technology use and in implementing innovations. In this case, employees' technological efficacy is vital to adopting and implementing technology. Another important technological factor associated with innovation and technology adoption is technology compatibility, which means the chosen technology should align with the organizational culture, values, general strategies, and policies. This is because management finds it simpler to adopt new technology when it is compatible with current systems and organizational processes [61]. Borgman et al. [62] emphasized the importance of other variables, including relative advantage and perceived complexity under the technology dimension of the TOE. As Abualrob and Kang [63] point out, complexity negatively affects technology adoption because more complex technology poses risks and may therefore be ignored. In situations where technology is considered complex, its adoption becomes problematic because the perceived drawbacks outweigh the expected benefits.

Based on the aforementioned factors noted from existing studies, this current study measured the technological factors influencing the use of digital technologies in South African construction organizations using existing defined variables, including availability of existing technological infrastructure, technological competence, technology compatibility, relative advantage, and perceived complexity.

Organization—the organizational dimension relates to the internal resources and structure of the organization that support the adoption of technologies [47]. This cuts across factors such as top management support, financial resource availability, organizational readiness, business size, organizational culture [51,53,54]. According to Low et al. [48], management support is associated with the creation of a favorable organizational climate, which is fostered by leadership vision and commitment. This is essential for any organization to adopt new initiatives [64]. It has also been noted that top management plays a significant role in adopting and disseminating e-workforce management systems because implementing new technologies usually entails organizational transformation that requires management readiness according to Al-Alawi et al. [65] and Teo et al. [66]. Furthermore, top

management provides companies with the necessary financial support needed to introduce new workforce management technologies [61].

Furthermore, organizational culture strongly influences the adoption of new technologies, which can facilitate workforce management in construction organizations [67]. Omran and Anan [68] noted that high-performing organizations with a proper organizational structure benefit most from implementing emerging technological solutions. It is noteworthy that the construction industry in South Africa lacks a culture of technology adoption, as the number of available technologies and the financial resources available are quite limited [69]. Previous studies indicate that factors such as organizational structure, size, financial capability, and innovativeness influence organizations' decisions to introduce certain technologies [64]. Organizational size can also significantly affect the extent of technology adoption and the types of technologies used. In general, the larger the organization, the more types of innovation it is likely to adopt. This tendency can be explained by resource abundance and the ability to manage risks and benefit from innovations, which help recoup costs [70]. However, construction businesses in many developing countries, including South Africa, are predominantly small- and medium-sized enterprises that are unable to adopt necessary technologies to improve their performance and service delivery due to high implementation costs [71].

Based on the aforementioned, this current study measured the organizational factors influencing the use of digital technologies in South African construction organizations using existing defined variables such as management support, organizational size and structure, financial capabilities, and innovativeness.

Environment—The environmental factor pertains to aspects of the industry in which an organization operates and plays a significant role in influencing the adoption of new technologies [72]. It is rooted majorly in the concept of institutional theory developed by DiMaggio and Powell in the 80s that postulates that the external environment in which an organization operates will exert certain pressure (coercive, mimetic and normative) on how they adopt innovative solutions [73,74]. This can be seen from the aspect of competitive pressure forcing organizations to mimic their competitors, or government support through regulatory frameworks and policies which exact some coercive pressure on organizations to adopt technological innovations [51–54,73].

According to Gutierrez et al. [75], one important aspect of the environment is the market and technology service providers, in which competitive pressures and supportive regulations have been found to play a critical role in encouraging the development and implementation of innovative tools [73,76]. Competitive pressures from competitors in the same industry force an organization to adopt technologies and gain a competitive advantage [77]. Similarly, favorable policies, laws, and regulations are important in shaping organizations' decisions to adopt technologies. Policies or laws favoring technology adoption can aid the process, since such organizations would have to comply with legal requirements regarding technology adoption [77]. Additionally, the government, as the largest customer in the construction industry, can encourage the adoption of digital technologies in its projects through appropriate legislation in many developed countries [76]. Government encouragement can also take the form of training, funding, tax breaks, workshops, infrastructure development, and awareness campaigns [78]. Moreover, reliable suppliers capable of providing accessible technologies are also necessary. Such suppliers should be credible enough to assist with implementing technologies. This includes training individuals in using the technologies [76].

Based on the aforementioned, this current study measured the environmental factors influencing the use of digital technologies in South African construction organizations using existing defined variables, such as competitive pressures, government regulations

and support, the availability of reliable technology suppliers, the nature of the construction industry, and data security.

It is imperative to note that although the TOE framework's three-dimensional structure is retained, the current study expands its scope of application to determine whether the explanatory strength of the TOE framework is consistent across all three dimensions in the project-based construction context of a developing country such as South Africa. This is because the project-based construction context, in terms of structural characteristics, differs from the contexts in which the TOE framework was first developed and validated, such as manufacturing and e-business settings [77]. As such, the current study focuses on the contextual dependence of TOE's dimensions and proposes that their significance may be contingent on several industry-specific factors, making a case for the context dependence of the importance of TOE theory's dimensions [47].

Based on the review of existing studies, the study further hypothesizes that:

H₁. *Technological factors significantly relate to the adoption of digital technologies for sustainable workforce management in construction organizations in South Africa.*

H₂. *Organizational factors significantly relate to the adoption of digital technologies for sustainable workforce management in construction organizations in South Africa.*

H₃. *Environmental factors significantly relate to the adoption of digital technologies for sustainable workforce management in construction organizations in South Africa.*

H₄. *The adoption of digital technologies significantly relates to effective and sustainable workforce management in construction organizations in South Africa.*

Figure 1 shows the hypothesized relationships measured in the study.

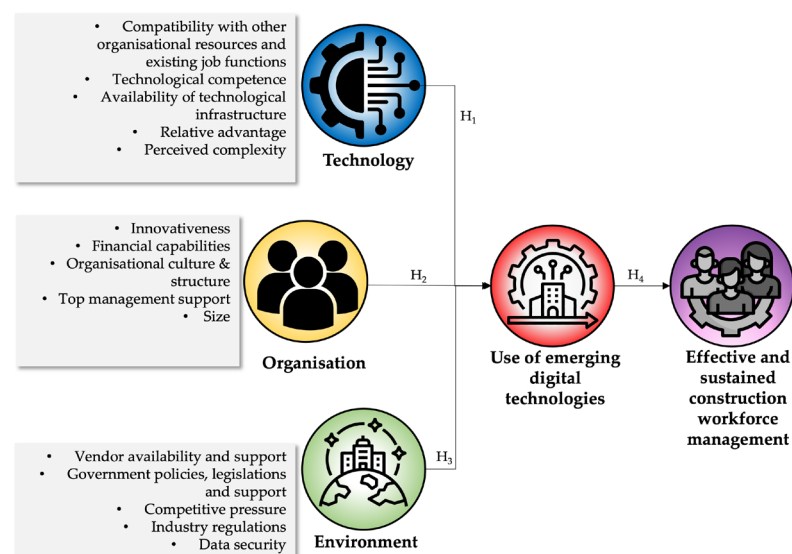


Figure 1. Conceptual framework of hypothesized relationships.

4. Methodology

The study is rooted in a post-positivist philosophy using quantitative research method. Data were gathered using a questionnaire, given its effectiveness in collecting data from large samples [79]. The respondents consisted of human resource practitioners and construction professionals holding managerial positions in construction organizations in Gauteng, South Africa. The choice of Gauteng as the study area was influenced by its relatively higher level of construction activity and greater number of organizations than in other regions of South Africa. The target population comprised 3630 construction organizations (main

and sub-contractors) based in the region [80]. Based on Yamane's formula for determining sample size at a 95% confidence level, a $\pm 5\%$ margin of error, and an estimated population proportion of 0.50, the calculated sample size was 360. However, it is important to note that the South African construction industry comprises many small- and medium-sized organizations [80], most of which lack designated human resource (HR) departments, which might have an impact on the number of HR experts in the sample. Based on this understanding, where an organization does not have a HR practitioner, only construction professionals involved in management activities (preferably workforce management) were approached to complete the survey. Based on this knowledge, purposive sampling was employed, and 182 participants (i.e., 50.6% of the targeted sample size) completed the survey electronically and were deemed fit for data analysis. Figure 2 provides an overview of the adopted research workflow.

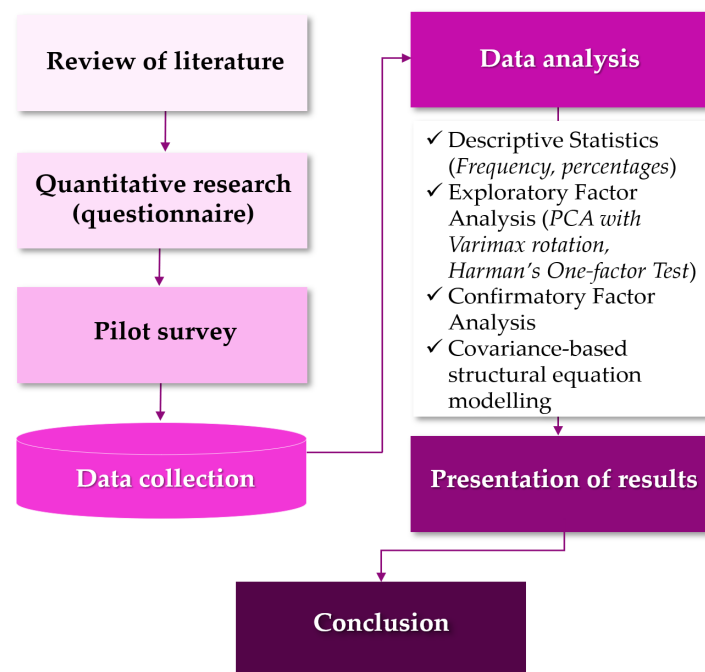


Figure 2. Research methodology overview.

The questionnaire had three parts: the first part gathered respondents' information, and the second part assessed the TOE factors influencing technology deployment, using 15 predefined variables drawn from existing studies and administered in the context of South African workforce management. The third part measured the potential outcomes of digital technologies on construction workforce management. Parts 2 and 3 of the questionnaire were measured using a five-point significance/influence scale ranging from 1 ("Very Low") to 5 ("Very High") as suggested in Vagais [81]. This questionnaire was distributed via Google Forms, sent via email and on social platforms such as LinkedIn, along with a cover letter that described the study's purpose, informed respondents that participation was voluntary, and assured them of anonymity. Furthermore, ethics approval was obtained from the University of Johannesburg's ethics committee before data collection (approval number UJ_FEBC_FEPC_00830). Fellows and Liu [82] have earlier emphasized the need to pilot a survey instrument to test if the questions in a questionnaire are intelligible and unambiguous. Thus, the questionnaire was piloted among seven participants (two human resource practitioners and five construction professionals). The final survey instrument was then modified based on the input received from the pilot study and distributed to the identified respondents. Background data were analyzed using frequencies (f) and

percentages (%). Reliability for sections 2 and 3 was assessed using Cronbach's alpha, yielding $\alpha = 0.882$ and $\alpha = 0.944$, indicating high reliability. For the data gathered on the envisaged outcomes of digital technology deployment on construction workforce management, exploratory factor analysis (EFA) was conducted to regroup the variables into more manageable subscales. Since the TOE framework is already defined, the variables employed in this study were confirmed using Confirmatory Factor Analysis (CFA) in EQS version 6.4, which offers fit statistics that accommodate the non-normality in questionnaire data. Also, covariance-based structural equation modelling (CB-SEM) was used to determine the relationships between the TOE variables and the level of digital technology use, as well as the potential outcomes of digital technology use on construction workforce management. It is important to note that, since the data gathered were cross-sectional, the analysis does not support causal inference but reflects an associative relationship among constructs in the proposed model. Furthermore, CB-SEM was adopted because of its theory-confirmatory nature, which allows the testing and validation of the existing theoretical framework, like the TOE adopted in this study, which has clear hypothesized relationships. CB-SEM is suitable when the purpose of the study is not to predict or explore relationships but to confirm the theory, thus yielding robust global fit indices that measure the overall goodness of fit between the covariance structure and the model. In addition, CB-SEM is more reliable for large samples and normally distributed data [83]. One of the major considerations in using CB-SEM is the ideal sample size, with many studies suggesting a range of 150–200 for a non-complex model [84,85]. The sample size of 182 in the current study falls within this threshold and fulfils the standard requirement of a 10:1 ratio of cases to estimated parameters for SEM [86].

Since all assessed variables were collected in a single survey at a single time point, this could introduce common method bias (CMB). To determine this, Harman's One-Factor Test was conducted prior to the CB-SEM. A threshold of less than 50 for the first factor's eigenvalue in EFA was set, as noted in a prior study [87]. As such, CMB is said not to exist if the derived eigenvalue for the first factor is below 50. For this study, values of 38.9 and 41 were derived from factors influencing technology use and the expected outcomes on workforce management, respectively. This result implies that none of the variables exhibited greater variance than the others, suggesting that CMB is not an issue. However, caution is warranted when interpreting the relationships among these groups of factors in the model presented in the study, as the approach does not establish causation. Therefore, future studies could employ longitudinal designs or draw on multiple data sources to address CBM.

5. Results and Discussion

5.1. Background Information of the Respondents

The analysis of respondents' background information revealed that engineers ($f = 68$), quantity surveyors ($f = 50$), and project and construction managers ($f = 36$) were best represented. On the other hand, human resource practitioners ($f = 16$) and architects ($f = 9$) were the least represented. Most of these respondents have bachelor's degrees ($f = 131$) and master's degrees ($f = 33$), with the lowest academic qualification being a national diploma ($f = 18$). Furthermore, the respondents were drawn from contracting ($f = 65$), consulting ($f = 89$) and government organizations ($f = 28$). In terms of years of experience, 30% ($f = 55$) of respondents have up to 5 years in the construction industry, while the remaining 70% ($f = 127$) have more than 5 years. These results show that the study respondents are well equipped, both academically and in terms of industry experience, to make logical contributions to the research questions.

5.2. Digital Technology for Efficient Construction Workforce Management

Since the adopted TOE variables were defined in the literature, confirming these factors to determine which variables were valid, reliable, and significant to retain, and which to eliminate, in pursuit of a good model fit, was deemed necessary. To this end, CFA was conducted using the Robust Maximum Likelihood (RML) estimation in EQS 6.4. The choice to adopt EQS was based on prior submissions indicating that most questionnaire data are non-normal [88]. Therefore, to cater for this non-normality in data, EQS offers RML, which gives a more robust chi-square (χ^2) called the Satorra–Bentler scaled chi-square ($S-B\chi^2$) [89]. The derived standardized coefficient (λ) for each variable was assessed as seen in Table 1. This λ reflects the construct validity of the variables, and a threshold of above 0.7 is considered acceptable [90]. However, Hulland [91] has earlier noted that a λ as low as 0.4 can be retained in a model if the importance of such a variable and its influence on the overall fitness of the model have been carefully ascertained. For this study, a threshold of 0.60 was adopted, and three of the environmental variables, vendor availability and support (EF1), industry regulations (EF4) and data security (EF5), did not meet this threshold and were subsequently deleted after careful assessment of their impact on the overall reliability of the model. Apart from these three variables falling below the threshold of 0.6 for the λ , they were also eliminated since they do not have any specificity concerning the adoption of digital technologies, and they lack justification in the South African construction context, as external pressures are predominantly shaped by government procurement policy and direct competitive dynamics rather than the broader market forces these items were designed to capture. From Table 1, the remaining 12 variables have λ values ranging from 0.64 (EF2) to 0.87 (EF3). As a result, construct validity is demonstrated since they meet the threshold requirement. Regarding internal consistency, which was assessed via Cronbach's alpha (α) and rho A (ρA), the requirements of the threshold were defined above 0.7 [84]. The calculated values include $\alpha = 0.882$ and $\rho A = 0.887$, both exceeding the required threshold and showing internal consistency. In addition, the variables' significance was assessed using their p -values and corresponding Z-statistics. From Table 1, all 12 variables are significant, as their Z-statistics exceed 1.96 ($p < 0.05$). This assertion about the variables' significance was further confirmed by the coefficients of determination (R^2), with thresholds of 0.26, 0.13, and 0.02 for acceptable, moderate, and weak, respectively [92]. According to previous research, acceptable R^2 values vary by field and study context; in some social science contexts, even $R^2 = 0.10$ can be sufficient [86]. From Table 1, all 12 variables examined are significant at the acceptable level, with R^2 ranging from 0.405 (EF2) to 0.756 (EF3).

The fitness of the retained 12 variables in the TOE group was assessed using standardized root mean squared (SRMR) with other supplemental fit indices, including Tucker–Lewis Index (TLI), Comparative Fit Index (CFI), Bentler–Bonnet Non-Normed Fit Index (NNFI), Gamma Hat, McDonald's Centrality Index (Mc), the goodness-of-fit index (GFI), Bollen's incremental fit index (IFI), and Root Mean Squared Error of Approximation (RMSEA) as suggested in Hu & Bentler [93]. An SRMR of 0.075 was obtained. This met the acceptable threshold of ≤ 0.08 as noted in past studies [90,93]. The $S-B\chi^2/Df$ derived from RML, with a cutoff of < 3.0 for a good fit, was 1.803. Also, the NNFI was 0.847, which is within the acceptable range of 0.60 to 1.00 [94]. The derived GFI, CFI, and IFI all indicated good fit, with values of 0.888, 0.889, and 0.896, respectively, all within the expected range of 0 to 1, with values closer to 1 being preferable. Also, RMSEA indicated a good fit (0.058), which is within the acceptable threshold of ≤ 0.08 [95]. Based on these results, it can be deduced that the 12 variables assessed are valid, reliable and fit to improve the increased uptake of digital technologies for effective construction workforce management.

Table 1. Factor loading, Z-statistics and internal consistency of the TOE factors.

Variable	λ	Z	Sig.	R ²
Technology				
Availability of technological infrastructure (TF1)	0.71	8.56	Yes	0.507
Technological competence within the organization (TF2)	0.80	6.26	Yes	0.633
Compatibility with other organizational resources and existing job functions (TF3)	0.86	8.34	Yes	0.733
Relative advantage of technology (TF4)	0.66	7.07	Yes	0.431
Perceived complexity of the proposed technology (TF5)	0.66	7.63	Yes	0.432
Organization				
Top management support (OF1)	0.67	7.09	Yes	0.450
Size of organization (OF2)	0.65	10.15	Yes	0.419
Organizational culture and structure (OF3)	0.69	10.81	Yes	0.48
Organization's financial capabilities (OF4)	0.75	9.68	Yes	0.558
Organizational innovativeness (OF5)	0.77	8.88	Yes	0.586
Environment				
Competitive pressure (EF2)	0.64	5.04	Yes	0.405
Government policies, legislation and support (EF3)	0.87	5.15	Yes	0.756
Use of technology				
Use of digital technologies within the organization (USE)	0.67	1.00	Yes	0.550

Note: Robust statistical significance at a 95% confidence level; λ = standardized coefficient.

5.3. Digitalization and Effective Construction Workforce Management Outcomes

Preliminary analysis revealed that the data gathered from the last section of the questionnaire were suitable for EFA, with a Kaiser–Meyer–Olkin value of 0.879 (above the 0.6 threshold) and a significant *p*-value of 0.000 for Bartlett's test of sphericity [96]. Table 2 shows that the communalities explained communalities ranged from 0.543 to 0.852, indicating good communalities. EFA was conducted using principal component analysis (PCA) with varimax rotation, given PCA's ability to identify and reduce a large set of variables into smaller, coherent subscales. As shown in Table 3, PCA revealed that the variables converged into four groups after 10 iterations, with eigenvalues above 1.0 and a cumulative variance of 70.3%. These four principal components were further renamed based on their latent similarities, as suggested by William et al. [97], and are discussed accordingly.

Table 2. PCA digital technology diffusion in workforce management.

Component								
Outcomes	1	2	3	4	Comm.	EV	% Var.	
Construction workers' involvement and productivity								
Increased construction workers' involvement and participation	0.792				0.744	10.3	51.7	
Improved construction workers' productivity	0.735				0.753			
Enhanced interpersonal trust in construction organizations	0.732				0.787			
Improved health and safety management	0.701				0.678			
Enhanced decision-making mechanism	0.679				0.694			

Table 2. *Cont.*

Outcomes	Component				Comm.	EV	% Var.
	1	2	3	4			
Increased knowledge, skills, and abilities of construction workers	0.651				0.752		
Effective performance evaluation of construction workers	0.579				0.686		
Better overall service delivery	0.567				0.691		
Construction workers' development							
Cost-effective training		0.743			0.724	1.4	7.1
Ease of tracking construction workers' progress		0.734			0.678		
Flexibility in training more construction workers at a time		0.698			0.756		
Efficient performance appraisal feedback process		0.676			0.731		
Ease of forecasting labor demand		0.616			0.623		
Timeous selection of construction workers for prompt training		0.536			0.586		
Compensation and information management							
Data management and critical analysis			0.718		0.662	1.2	6.0
Ease of payment of compensation			0.716		0.686		
Ease in designing compensation packages and reward systems			0.667		0.715		
Shift from traditional workforce management strategies			0.588		0.714		
Talent attraction and retention							
Ease of attracting and retaining talented and diverse construction workers				0.870	0.852	1.1	5.5
Ease of selecting talented and diverse construction workers				0.550	0.543		

Note: Rotation converged in 10 iterations; EV = Eigenvalues; Var. = variance; Comm. = Communalities.

Table 3. Factor loading, Z-statistics and internal consistency of the grouped outcomes.

Variable	λ	Z	Sig.	R ²
Construction workers' involvement and productivity				
Effective performance evaluation of construction workers	0.76	8.23	Yes	0.57
Improved health and safety management	0.77	8.42	Yes	0.59
Increased construction workers' involvement and participation	0.78	8.59	Yes	0.61
Improved construction workers' productivity	0.86	3.07	Yes	0.74
Enhanced decision-making mechanism	0.81	9.17	Yes	0.57
Increased knowledge, skills, and abilities of construction workers	0.75	8.11	Yes	0.56
Better overall service delivery	0.74	7.88	Yes	0.54
Enhanced interpersonal trust in construction organizations	0.70	7.35	Yes	0.49
Construction workers' development				
Timeous selection of construction workers for prompt training	0.67	6.68	Yes	0.67
Flexibility in training more construction workers at the same time	0.87	9.72	Yes	0.57
Cost-effective training	0.82	8.79	Yes	0.45
Ease of tracking construction workers' progress	0.76	7.84	Yes	0.57
Ease of forecasting labor demand	0.67	6.61	Yes	0.45

Table 3. *Cont.*

Variable	λ	Z	Sig.	R ²
Efficient performance appraisal feedback process	0.78	8.13	Yes	0.60
Compensation and information management				
Ease in designing compensation packages and reward systems	0.80	7.43	Yes	0.64
Data management and critical analysis	0.76	6.98	Yes	0.58
Ease of payment of compensation	0.82	7.58	Yes	0.67
Shift from traditional workforce management strategies	0.77	4.90	Yes	0.59
Talent attraction and retention				
Ease of attracting and retaining talented and diverse construction workers	0.58	3.45	Yes	0.34
Ease of selecting talented and diverse construction workers	0.91	5.65	Yes	0.83

Note: Robust statistical significance at a 95% confidence level; λ = standardized coefficient.

Component 1—‘Construction workers’ involvement and productivity’—The first principal component accounts for 51.7% of the total variance. This component has eight variables, which are increased construction workers’ involvement and participation, improved construction workers’ productivity, enhanced interpersonal trust in construction organizations, improved health and safety management, enhanced decision-making mechanism, increased knowledge, skills, and abilities of construction workers, effective performance evaluation of construction workers, and better overall service delivery. Based on the similarity in the variables, the component was named ‘construction workers’ involvement and productivity’. It has been noted that involving employees in decision-making and development activities relevant to their positions within an organization can lead to significant motivation and employee commitment [98]. Moreover, employee engagement increases work satisfaction, motivation, and dedication, as workers feel more engaged in achieving organizational objectives [99]. This ultimately leads to increased productivity in the organization. Therefore, construction organizations in South Africa seeking to improve their workforce management will gain an advantage by adopting digital technologies to transform their business functions.

Component 2—‘Construction workers’ development’—The second principal component accounts for 7.1% of the total variance explained and has six variables loading on it. These variables are cost-effective training, ease of tracking construction workers’ progress, flexibility to train more construction workers at a time, an efficient performance appraisal and feedback process, ease of forecasting labor demand, and timely selection of construction workers for prompt training. Subsequently, these variables were named ‘construction workers’ development’. This finding shows that construction organizations can further develop their workers through digital technologies. Past studies have noted that employee training and development are vital to workforce management [100], as trained employees facilitate companies’ achievement of their objectives [101]. Having a cost-effective training process is essential to encourage an organization’s investment in its workforce’s training. Also, Neeraj [102] noted earlier that technological innovations, such as online meeting platforms, enable a more technical and cost-effective approach to employee training. Through these platforms, more employees can be trained simultaneously, and employee progress can be easily tracked. This is because these digital platforms provide ease of use, data retention, knowledge distribution, opportunities to improve data, and the convenience of employee training [103]. Therefore, if construction organizations in South Africa are to make a significant difference in developing their workforce, digital platforms such as online meetings, advanced gamification, and virtual and augmented reality are

essential. These technologies offer new ways to present information and training materials to users, thereby creating a new approach to effective learning.

Component 3—‘Compensation and information management’—Four variables converged on the third principal component, accounting for 6% of the explained variance. These variables are data management and critical analysis, ease of paying compensation, ease of designing compensation packages and reward systems, and a shift from traditional workforce management strategies and activities. This component was named ‘compensation and information management’. This finding shows that by digitalizing business functions and adopting digitalized information systems, managers in construction organizations can have direct access to relevant data of their workforce. Adequately analyzing these data through big data analytics and storing them in cloud storage platforms can facilitate easier management of employee information and faster decision-making, particularly for classifying and reclassifying employees [104]. In addition to managing employee data, another important factor is creating an effective compensation and rewards program for staff members. Evidently, a poorly structured compensation program may result in wages that are too high or too low, thereby affecting employability [105]. Digitalization offers an easier way to design and administer this compensation and reward packages. The study by Tripathi and Singh [24] aligns with this submission, noting that digital software enables managers to oversee the compensation process and implement effective changes as needed.

Component 4—‘Talent attraction and retention’—The last principal component accounts for 5.5% of the explained variance and includes two variables: ease of attracting and retaining talented and diverse construction workers, and ease of selecting them. This component was subsequently named ‘talent attraction and retention’. Past studies have noted that the quality of employees within any organization depends heavily on the efficiency of the recruitment and selection process adopted [106]. The findings of this study show that digitalization can make this process easier by improving the attraction, selection, and retention of required talent within organizations. A similar observation was made by Brandão et al. [35]. Construction organizations can adopt several online platforms for recruitment and selection. Some of these platforms allow organizations to assess applicants and easily exclude those who do not meet the criteria for the vacant position from the process.

The results in Table 3 revealed that the assessed outcomes ranged from 0.58 to 0.91, indicating good construct validity, as the variables explained more than 50% of the model’s total variance. α and ρ_A show good reliability, with $\alpha = 0.949$ and $\rho_A = 0.960$. The variables in each group were also significant, as their Z-statistics are well above 1.96 ($p < 0.05$). Further confirming the significance of these variables, the derived R^2 values exceeded 0.5 for most variables, except for 4. The fitness of these groups was also assessed. The SRMR was 0.063, below the ≤ 0.08 threshold, and the RMSEA was 0.025, also below the 0.05 threshold. Other supplementary fit indices indicated a good fit, with CFI = 0.989, and IFI = 0.990, as these values are close to 1. GFI of 0.755 was derived. This result might be considered a bit low and may be associated with model complexity because the GFI tends to exhibit bias in estimates of model fit when a model includes many parameters [86]. However, other fit indexes (CFI, IFI, RMSEA, SRMR) indicate a satisfactory model fit. The NNFI also had a value of 0.987, within the acceptable threshold of 0.60 to 1.00. The result implies that the outcome groups derived from EFA are suitable for adoption.

5.4. Structural Model Assessment

Based on the attainment of appropriate internal consistency, reliability, and model fit for the assessed TOE factors, and the identified outcome groups, the structural relationships among the TOE, the deployment of digital technologies and the possible outcomes on construction workforce management were assessed. Using the path coefficient (β) along with

the Z-statistics and p -values derived from the RML estimation, the structural relationship was evaluated. In Figure 3, a path significant relationship is denoted by a solid line, while a non-significant path relationship is denoted by a dashed line. Also, the double asterisk (**) denotes a p -value significant at ≤ 0.05 , while the triple asterisk (***) denotes a p -value significant at ≤ 0.001 . Figure 3 shows that the technology has the highest β -value (0.58) and a significant Z-value of 4.207. This result implies that the technology dimension will have a 58% significant relationship with the uptake of digital technologies for effective construction workforce management in the study area. Similarly, the environmental dimension shows a significant 19% relationship, with a Z-value of 1.967. However, the organizational dimension revealed a β -value of 0.10 and a Z-value of 0.057, which is less than the 1.96 cutoff (i.e., $p < 0.05$). This implies that the organizational dimension does not significantly relate to the deployment of digital technologies for effective construction workforce management in the South African context. This result may be because workforce management is already an organizational function, and respondents do not consider it a critical factor compared with the other two groups. Further assessment of the relationship between the use of these technologies and the envisaged outcomes on construction workforce management revealed a β -value of 0.61 (61%) with a significant Z-value of 4.545. This implies that technology and environmental factors are significantly related to how construction organizations in South Africa use emerging digital technologies, which, in turn, is significantly related to the attainment of the four possible groups of outcomes. Having established the significance of the paths in the model, the predictive power was measured using the derived overall R^2 . The results revealed acceptable predictive power of 0.412 for the level of use and 0.372 for the envisaged outcomes on construction workforce management. This implies that the variables retained in the TOE have an acceptable level of predictive power for how technologies are used and how this relates to the overall management of the construction workforce in South Africa.

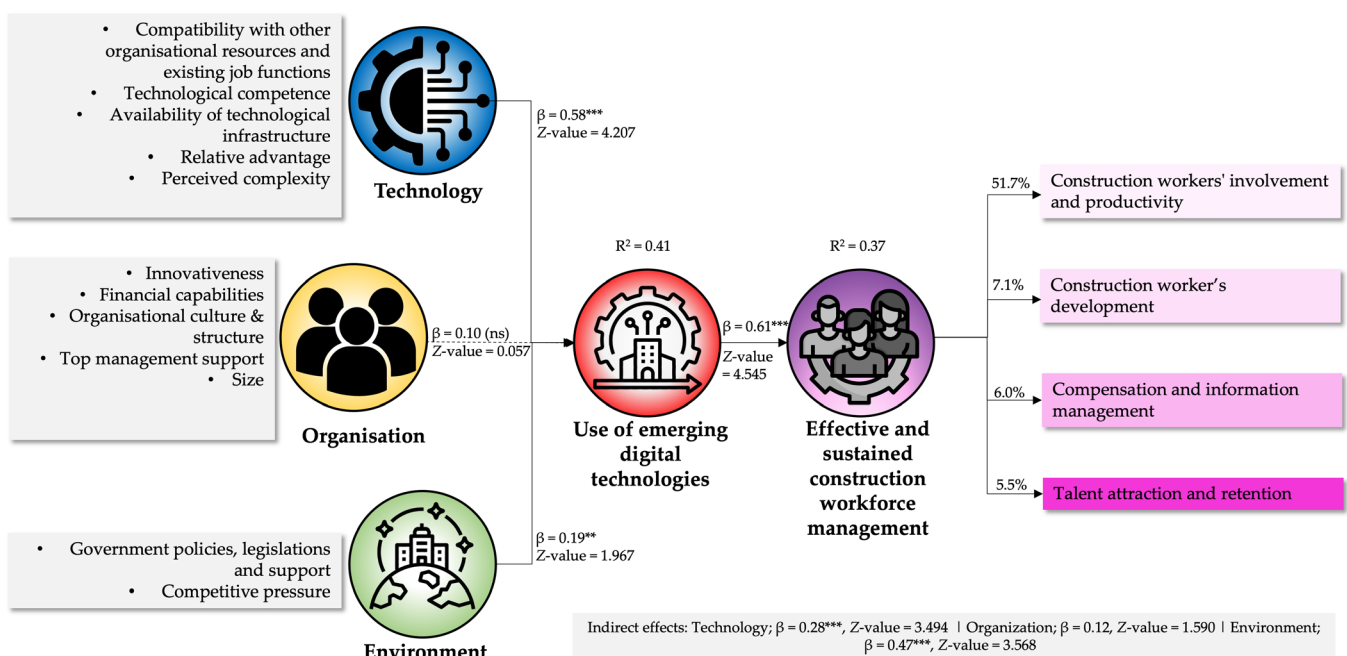


Figure 3. Emerging digital technologies and construction workforce management nexus.

Given that the 'use of digital technologies' construct was introduced as a mediator in the model, the indirect relationship between TOE and effective workforce management was further assessed by examining the derived β -value, Z-statistic, and p -value. The result shows a positive and statistically significant indirect effect of the technology dimension

on the workforce management outcome variables via effective use of digital technology ($\beta = 0.28$, $Z = 3.494$, $p < 0.001$). This suggests that technological factors, including compatibility, competence, infrastructure, relative advantage, and complexity, affect workforce management outcomes not directly, but by making effective digitalization possible. Similarly, there is a positive and statistically significant indirect effect of the environment dimension on the workforce management outcome variables through effective digital technology use ($\beta = 0.47$, $Z = 3.568$, $p < 0.001$). The implication of such an indirect effect is that government policies, legislation, support, and competition increase workforce management outcomes by influencing effective digital technology use. This is the most powerful indirect effect among the three dimensions, underscoring the importance of external environmental enablers in achieving the effects of digitalization on workforce management outcomes. At the same time, there is no significant indirect effect of the organization dimension on the outcome variables ($\beta = 0.12$, $Z = 1.590$, $p > 0.05$), which is in accordance with the absence of a significant direct relationship ($\beta = 0.10$, ns). In other words, organizational factors do not influence the workforce management outcomes neither directly nor indirectly through digitalization. Overall, the mediation analysis empirically demonstrates that effective use of digital technology mediates the relationship between technological and environmental enablers and effective and sustainable construction workforce management outcomes.

5.5. Implications of Findings

The study found that integrating digital technologies to enhance construction workers' management in South Africa is significantly associated with specific technological and environmental factors, as posited by the TOE framework. The most important technological factors include compatibility between the technology and the organization's resources and activities, technological competence, technological infrastructure, relative advantage, and the complexity of the proposed technology. Consistent with past studies, it is vital for construction organizations to deploy digital technologies that are compatible with other available resources, particularly human resources, and that are easy for employees to use, given their required technological competencies [60]. Compatibility is especially important because possessing the skills needed to manage technologies creates an enabling environment for construction organizations to maintain a competitive advantage over their rivals.

From an environmental perspective, factors such as government policy, support, legislation, and competitive pressures are important determinants of the adoption of digital technologies to improve workforce management among construction organizations. It is impossible for construction organizations to work in isolation; their operations are determined by prevailing policies and regulations [73]. As one of the largest clients in the construction industry, the government has a major influence on facilitating the adoption process through various measures, such as training, financial aid, tax breaks, workshops, and raising awareness of innovative initiatives. Consistent with findings from the existing literature, government support takes the form of training facilities, financial aid, tax reductions, and raising awareness [77,78]. Besides government support, competitive pressures are also significantly associated with the adoption process. When the competition improves workers' management through innovation, others are forced to imitate it [73,76,107]. Therefore, construction organizations should consider competitive pressures as a means of encouraging the integration of emerging technologies into their workforce management processes.

Contrary to expectations based on the TOE construct, the findings show that the Organizational dimension was not a significant predictor of the effective use of digital tools for sustainable workforce management ($\beta = 0.10$, $p > 0.05$). There are several explanations of the unexpected result that are valid for the South African construction context. The industry in South Africa comprises many fragmented enterprises, with a high prevalence of small

and medium organizations and temporary, project-based units [71]. Consequently, typical organizational variables of the TOE, such as organizational innovativeness, structure, culture, and prominent top-management support, may be irrelevant in this case. Decisions regarding the digitalization processes are often spontaneous or dictated by clients' or projects' demands, and thus they shift the impact onto Technology and Environment dimensions [108]. The effect of organization can take place indirectly (e.g., via compatibility with other organizational resources and existing job functions), resulting in insignificant direct path in the model. Additionally, focusing on the technical and environmental dimensions, such as technology availability, regulatory pressures, and competitive environment, might overshadow organizational initiatives. Organizations may be more reactive than proactive because digital technologies are adopted more in response to specific situations than as a result of strategic discussion [109]. Moreover, there may be problems with measurement validity as organizational variables developed for advanced economies might not apply in this context. Evidently, this result suggests that when it comes to the implementation of digital tools for the sustainable management of the workforce within the South African construction industry, technology and environmental factors play a greater role than organizational factors do. This submission is consistent with the project-based nature and often-informal approach to management that prevail in the industry and highlights the importance of intervention at the industry level [18,110].

Based on the results of the study, the deployment of digital technologies in construction organizations in South Africa can lead to a number of advantages: (1) increase the engagement and productivity of workers; (2) improve the development of personnel in the construction industry; (3) optimize workforce management and compensation management; and (4) attract and retain talent. Construction organizations in South Africa face several challenges, including low worker productivity, skill shortages, and health and safety concerns [12]. Thus, it is necessary for managers to digitalize organizational processes to achieve higher productivity and better project outcomes. Globally, the construction industry is often perceived as dangerous, which discourages young people from entering it [111]. This perception of the construction industry leads to a skills shortage. According to the study's findings, digital technologies will help create a safer environment; thus, managers and construction firm owners should embrace these tools. This will make it possible to improve worker safety. Digital solutions, like drones, sensors, and robotics, will help perform tasks remotely and minimize hazards. Furthermore, augmented, virtual, and mixed reality can enable immersive learning experiences for workers. Moreover, cloud computing and big data analytics will facilitate information exchange, thereby increasing worker productivity. To promote the adoption of digital technologies, top management at construction firms should consider revising their company policies to support these solutions. This step is important because digital culture and policy become barriers to digital transformation [112]. Hence, it is proposed that there would be considerable benefits to making changes in the digital culture and policy. Another important player in the process of digitalizing construction companies is the industry's regulatory bodies, which can set regulations that encourage or require industry participants to adopt digital technologies.

In view of the above findings, there exist several implications for construction organizations, HR managers, and the policymaking process in South Africa. From the construction organization perspective, it is important for organizations to focus on adopting technologies that align with their resources and are easy to use, rather than pursuing the most advanced technology available. All adopted technologies should be introduced alongside competence-building through proper training and a staged rollout. Moreover, organizations (especially small and medium-sized) should take early use of digital solutions as an opportunity for competitive advantage, given the importance of competitive pressure

revealed through the study. Even though organizational factors were not found to have any statistically significant effects, this does not mean their absence; therefore, firms should make changes to their internal policies and technology adoption culture. As for practical tools, it would be worth prioritizing drones, sensors, and robotics to increase site safety; AR/VR technologies for low-risk, immersive workforce training; and cloud computing and data analytics for payroll and compensation control and information management.

For HR managers within construction organizations in South Africa, digitalization should be viewed from the perspective of a strategy of attracting and retaining staff in view of the industry problems with attracting young people due to safety reasons. Digital literacy and knowledge of digital tools should be components of employee onboarding and professional development. It would be reasonable to use digital solutions to manage employee compensation and track performance. It would also be helpful to involve project-level managers in introducing new technologies, since decisions about adoption are made at this level.

For policymakers, the government's role as a market regulator and a major client of the industry is crucial. The governmental support measures (training subsidies, tax benefits, awareness campaigns) should be strengthened and tied to technology adoption. It would be reasonable to include companies' digital capabilities as a criterion for scoring in public tenders, thereby transforming competitive pressure into policy. Taking into account the fragmented, informal, and project-based nature of the sector, it seems impossible to change the situation with the help of voluntary actions of firms and therefore, regulators should introduce minimum requirements for the use of technologies via a contractor registration system handled by South Africa's Construction Industry Development Board (CIDB) and provide different support options according to the size of businesses and informality of their structure.

6. Conclusions

In conclusion, following the use of the TOE framework and CB-SEM analyses, the results show that certain technological and environmental factors, such as compatibility, technological competency, relative advantage, ease of use, government policy, legislation, support, and competition, play an important role in the adoption and effective use of digital technologies for workforce management. It is noteworthy that the organizational dimension was found not to be a relevant predictor for the adoption of digital technologies in the South African construction industry, and the reason for that lies in the fact that the industry is highly fragmented, informal and project-based; thus, digitalization in this industry is often dictated by the needs of the particular projects or clients rather than organizational strategy.

This study contributes theoretically to the existing discourse on construction workforce management in the era of pervasive technologies. It applies the TOE framework to a rather unexplored domain of digitalization within the construction industry of a developing country. From the perspective of TOE, this study shows that digitalization can be used to bridge TOE drivers of adoption and outcomes of effective and sustainable workforce management. The study further revealed that the technology and environment dimensions play a crucial role in helping organizations manage their workforces digitally while the organizational factor shows little explanatory power due to the fragmented and project-based nature of the construction industry. The finding challenges the assumed dimensional equivalence that underpins traditional TOE models and calls for a boundary-conditioned application of TOE in further research on digitalization in construction, especially in developing economies.

In practice, these findings have important implications for various actors in the South African construction industry. The findings remind HR managers and construction organizations of the importance of technology compatibility, usability, and the development of necessary skills. Also, these findings show that organizational restructuring alone is not enough for technology adoption, which means that there should be some facilitating factors involved. The findings further encourage the relevant government officials to introduce a combination of incentives and control over technology adoption. Thus, the Department of Public Works and Infrastructure should find ways to provide financing for the digital transformation of small and medium construction organizations via grants, low-interest loans, and tax incentives. Also, the South African Construction Industry Development Board should mandate digital workforce management during the registration and tendering process, and the Construction Education and Training Authority should finance workforce management training at TVET colleges. Finally, the Department of Employment and Labor should include digital workforce management in the Occupational Health and Safety Act.

Despite the study's practical and theoretical contributions, some limitations remain. For instance, the study's findings are limited by the quantitative methodology used, which captured objective, generalizable relationships between variables but not the subjective experiences underlying them. Therefore, future research should explore them using a qualitative or mixed-methods approach. Also, the study analyzed cross-sectional data, making it difficult to establish causal relationships among variables. A longitudinal design is therefore suggested for future studies. More so, the findings of the study cannot be generalized to the entire South Africa as the data were drawn from one province. Future studies are therefore recommended in other provinces to compare findings and expand the sample.

Author Contributions: Conceptualization, B.P.M. and L.A.; methodology, B.P.M., L.A. and D.A.; software, B.P.M. and D.A.; formal analysis, L.A. and D.A.; investigation, B.P.M. and D.A.; resources, D.A. and C.A.; writing—original draft preparation, B.P.M., L.A., and D.A.; writing—review and editing, D.A. and C.A.; visualization, D.A.; project administration, D.A. and C.A.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no funding.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and was approved by the Faculty of Engineering and the Built Environment Ethics Committee of the University of Johannesburg (protocol code UJ_FEBE_FEPC_00830; approved on 5 June 2023).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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