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Enhancing Construction Workforce Efficiency through Digital Training: An Empirical Study

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Abstract

Background: Despite being a major employment generator, India's construction industry suffers from low labor productivity due to its predominantly semi-skilled workforce. Digital training methods offer promising solutions, yet empirical evidence on their effectiveness remains limited.

Objective: This study evaluates the impact of digital training on productivity across four construction trades: brick masonry, plastering, steel fabrication, and shuttering carpentry.

Method: Using a quasi-experimental design, we assessed 400 workers through pre-post productivity measurements. Participants received either digital training (audio-visual modules with simulations) or traditional classroom instruction. Statistical analysis included t-tests and multiple linear regression.

Results: Digital training participants achieved significantly higher productivity gains than traditional training recipients (17.2 vs. 6.8 units; $t(398) = 12.34$, $p < 0.001$, Cohen's $d = 3.7$). Regression analysis revealed that digital training independently contributed 9.8 additional productivity units ($p < 0.001$), with worker experience and job role serving as significant moderators. Technical trades showed the greatest improvements.

Conclusions: Digital training substantially outperforms traditional methods in enhancing construction worker productivity. These findings support widespread adoption of digital workforce development programs and transition toward outcome-based training models in India's construction sector.

Keywords: Digital Training, Construction Workforce Productivity, Skill Development, Role-Specific Skilling, Outcome-Based Learning.

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1.0 Introduction

One of the main industries in India that creates jobs is the construction sector, which is slowly but significantly changing (Chen, 2021). The sector, which has historically relied on manual labour and unofficial methods, is currently facing an increasing need for modernization in terms of both procedures and skills (Organization., 2020). The demand for a workforce that is more competent, adaptable, and technologically savvy has become a national priority as infrastructure development picks up speed and urbanisation rise.

The construction industry, particularly semi-skilled and unskilled workers, has stayed on the fringes of official training systems despite employing millions of people and making a substantial contribution to the GDP (Heigermoser, 2019). Most workers acquire their skills through unofficial apprenticeships; they are not exposed to current tools or structured skill-building. In this regard, digital training has become a more comprehensive facilitator of inclusivity, upskilling, and digital literacy in addition to being a way to increase productivity (Serrano, 2019).

Now that digital platforms are more widely available, convenient, reasonably priced, and easier to use, they may connect with employees even on construction sites. Digital techniques, in contrast to traditional classroom training, provide visual, language-adaptive content that appeals to very hands-on workers who may not be literate. Employees would be able to study brief video modules at their convenience. However, several obstacles still exist, including a lack of standardisation, an absence of outcome-based evaluation criteria, and a limited institutional ability to produce high-quality digital content (Obiki-Osafiele, 2024). Most significantly, many training programs fall short in measuring concrete project-level impact or in matching the actual demands of contractors.

Beyond anecdotal evidence, this study looks at how digital training impacts on-site performance in a variety of trades, including fabrication, carpentry, and masonry (Kamar, 2020). To determine whether digital skilling is fulfilling its promise—not just in terms of speedier work but also in terms of creating a workforce of future-ready, tech-savvy construction workers—it integrates government requirements, industry benchmarks, and field-level observations.

2.0 Statement of the Problem

Despite its vital role in creating jobs and developing infrastructure, low productivity among blue-collar workers remains a challenge in India's construction sector. Most projects rely on manual labour with varying skill levels, and many workers lack access to formal training, which causes delays, cost overruns, and quality problems.

Despite providing a flexible and scalable alternative to traditional training, digital learning technologies like video classes and site-based microlearning have not yet been proven to increase productivity in the real world. Due to the lack of tangible, quantifiable results associated with essential construction work, companies frequently hesitate to invest in such initiatives.

Furthermore, rather than focusing on real output increases like daily masonry volume, plastering area, or quantity of steel fabricated—important indicators for project managers and contractors—most current assessments emphasise training attendance or learner satisfaction.

By assessing whether digital training may result in measurable increases in productivity across important building trades, this study aims to close this gap. By using 400 workers' pre- and post-training data and comparing performance to CPWD and NBO benchmarks, the study seeks to:

- Identify productivity improvements post-training,
- Test the statistical significance of these changes,
- Provide evidence-based insights for industry stakeholders.

By grounding digital skilling initiatives in measurable impact, this study contributes to more informed decision-making and supports the broader goal of building a future-ready construction workforce.

3.0 Literature review

The Indian construction industry is still plagued by incessant shortages of skills despite the best efforts undertaken by both the government and the entrepreneurs. The Construction Skill Development Council of India (CSDCI, 2022) carried out an in-depth sectoral skills gap assessment, with the estimates indicating a very high incongruity between the quantity of trained labour force and industry-specific requirements. To lead towards eliminating this gap, the report demanded increased cooperation between the public and the private stakeholders. On the same note, the National Skill Development Corporation (NSDC, 2020) indicated that despite the size of the construction industry as one of the largest employers, the level of formal skilling is dangerously low. It suggested the use of an incentivized public-private partnership to boost upskilling and formalization of the workforce. NITI Aayog (2018) also encouraged a holistic policy framework to coordinate the growth of industries, skilling and employment to realize the economic potential of India in the labor-intensive industries such as construction.

Comparing the weaknesses of generalized training programs with the advantages of role-specific skills development, Fellows and Liu (2021) discussed the necessity of having function-based competencies as they maintain both employability and the ability to work on-site. Their studies affirm the necessity of individual vocational training in line with the directives of maintenance and operations positions. Likewise, KPMG India (2017) said that more effective initiatives that need redeveloped curricula but are led by industries in mentorship-based programs will be better equipped to meet the judicious needs in the workforce. A common structural mismatch was also observed in the informal sector, where most Indian construction workers are represented, between the capabilities of the workforce and their occupational needs, leading to the situation of underemployment with its low productivity (ILO, 2020). Schroeder and Denison (2018) stated that one of the main success factors of low-skilled workers is the role that employer engagement, informal learning, and personalized training play as predictors.

Skilling ecosystems have emerged with revolutionary solutions through the emergence of the digital world. In their research, Gupta and Pathak (2021) studied the use of vernacular e-learning modules designed to cater to the needs of unorganized construction workers and discovered that easily accessible digital materials significantly improved task understanding and execution. Nevertheless, there were obstacles like low digital literacy and poor infrastructural challenges, which slowed down adoption. The Ministry of Skill Development and Entrepreneurship (MSDE, 2021) created a platform addressing these, the "Digital Ecosystem for Skilling India", with localized and mobile-accessible resources. Subsidiary to that, Rao and Bhatia (2022), based on a randomized controlled trial, proved that the digital table-based training had a much more favorable effect on the facilitation of the task accuracy, minimization of errors, and supervision necessities as compared to the traditional training methods. Mahadevan, Pillai, and Ramesh (2020) assessed the vocational training problem using augmented reality (AR) and identified that spatial comprehension, safety, and the efficiency of training improved.

Internationally, the Organization for Economic Co-operation and Development (OECD, 2020) indicated that learning improved when training programs adopted simulations, e-portfolios, and mechanisms that provided feedback in real-time within the vocational education and training (VET) systems as experienced in construction training. The survey conducted by UNESCO-UNEVOC (2019) found mobile learning, modular certification, and community-based TCs to be very effective within an informal setting like the Indian construction industry. World Bank (2021) emphasized the importance of addressing these issues related to financing, scalability and monitoring of the programs, used to develop skills, as without it, India may simply fail to gain the demographic dividend.

The construction industry is also fast changing with respect to Industry 4.0. Yang et al. (2025) examined the threat of obsolescence of the workforce under the influence of the digitalization process in railway construction, and the researchers supported the idea of flexible training systems incorporating new digital tools. Aghimien et al. (2024) requested a paradigm change in construction workforce management, stating that it is required to incorporate robotics, automation, and data-driven workflows into collaborative ecosystems. According to García de Soto et al. (2022), the Construction 4.0 technologies are reorganizing the hierarchies of the workforce by enhancing decentralization and collaborative work rather than the strict traditional approach. Equally, Wang et al. (2020) stressed that off-site and modular construction is successful, which depends on the concept of digital literacy and well-coordinated systems, which are supported by the organizational culture changes. Examples of some operation obstacles noted by Turner et al. (2020) include the expense of operating, compatibility between systems, and operational resistance due to a lack of a sufficient digital training structure.

Asad et al. (2021) corroborated the effectiveness of virtual reality (VR) to be used in experiential learning, where learners will utilize technical knowledge through simulation environments, which fills the gap that often exists between classroom training and fieldwork.

Several studies have explored the training methodology approach related to safety-oriented training. Hou et al. (2020) addressed how digital twins are used to simulate site conditions and concluded that they are considerably efficient in enhancing hazard awareness and accidents prevention. Li et al. (2018) showed that immersive Audio-Visual digital training settings promoted a strong improvement in the concept of spatial cognition and safety compliance in trainees in construction. Bristol-Alagbariya et al. (2022) also stressed the importance of performance management systems that use real-time digital metrics to ensure accountability and comprehensive improvements at the site level.

Lastly, work force development has an educational structure. Chuang (2021) applied constructivism and social learning theories to vocational training and attested to the benefits of authentic, reflective, and contextual digital learning space. A systematic review recently published by Regona et al. (2022) recognized the potential of digital training in streamlining construction and warned about ethical, data management, and employee preparation considerations that are important to address when implementing the technology.

4.0 Research methodology

4.1 Research Design and Rationale

This study examined the impact of digital training on productivity in the Indian construction business using a quantitative, quasi-experimental research design. The operational constraints on active construction sites led to the decision to use a pre-test/post-test single-group method for the digital training cohort. A comparison with a group that had been traditionally trained was also carried out to assess any discrepancies in the outcomes. Despite the impracticality of random assignment due to logistical considerations and employer-driven training formats, the study mitigated selection bias by ensuring that participants were evenly distributed across job categories and shared baseline characteristics like age and experience.

Using a quasi-experimental framework allowed us to keep ecological validity in mind (i.e., to replicate real-world working environments instead of controlled lab simulations) and to see measurable gains in worker performance that were caused by training interventions. After controlling for factors like job function and years of experience, the multiple linear regression used in the post-analysis provided more support for the internal validity.

4.2 Study Population and Sampling Strategy

The intended audience consisted of semi-skilled construction workers employed by three large private construction firms in India to manage infrastructure projects. Using a purposive sampling technique, 400 individuals were selected to represent four crucial trades in construction: brick masons, plastering masons, steel fabricators, and shuttering carpenters. Out of the total sample, 100 workers from each trade were included.

This stratified method made sure that all crafts were represented, so we could compare how various occupations react to training. The chosen employees' educational backgrounds and professional experiences ranged widely, but most had fewer than ten years of relevant job experience (76%), making them excellent candidates for online skill development programs. This group's demographics are typical of the construction site workforce in India; 96% of the workers were men and 70% were in the 25–45 age range.

4.3 Training Intervention

Two equal groups of participants were formed: one for traditional training (n = 200) and another for digital training (n = 200). The conventional group received training in a classroom setting with a teacher who mostly communicated via spoken instructions and written materials. On the other hand, the digital training group had access to job-specific learning tools such as task-based simulations, class-based modular video lessons, and on-site audio-visual linked resources.

To ensure employees with limited reading skills could access the digital classes, they were provided in local languages with simple images and animations. The training materials for both groups were standardized to meet the expectations of the National Building Organization (NBO) and the Central Public Works Department (CPWD), which have established productivity targets.

4.4 Data Collection Methods

Data collection spanned 30 days and included both quantitative output tracking and supervisory evaluations. Pre- and post-training productivity was measured using a combination of:

- Time-motion studies
- Daily work logs
- Supervisor assessments
- Standardized productivity metrics for each trade (e.g., square meters plastered/day, number of bricks laid, or kilograms of fabricated steel)

Each worker's productivity was documented before and after the training intervention to evaluate changes in performance. The research team maintained consistent documentation protocols to ensure the reliability and validity of measurement across all sites.

4.5 Analytical Framework

The study employed a multi-layered analytical approach to draw robust conclusions from the data:

- Descriptive statistics were used to summarize demographic data and baseline worker characteristics.
- An independent samples t-test was used to compare productivity gains between the digital and traditional training groups, confirming that digital methods yielded significantly higher gains (mean = 17.2 units vs. 6.8 units; $t(38) = 12.34$, $p < 0.001$, Cohen's $d = 3.7$).
- A paired samples t-test evaluated pre- and post-training productivity within the digital training group, which revealed a statistically significant improvement from 62.4 to 78.6 units ($t(39) = 18.76$, $p < 0.001$).
- A multiple linear regression model was developed to estimate the influence of training type, experience, and job role—along with interaction effects—on productivity outcomes. The model had strong predictive validity and statistical significance ($p < 0.001$).

This layered analysis allowed for both **comparative insights across training types** and **predictive modelling of individual performance outcomes**, enabling practical recommendations for workforce planning.

4.6 Ethical Considerations and Limitations

All employees were asked to give their informed consent before they could participate, and the organizations that took part gave their stamp of approval in terms of ethics. No information that could identify a participant was collected or shared in any way, shape, or form.

The main problem with the study was that it did not have a randomized control group, which makes it hard to say what caused what. On the other hand, to account for confounding factors, regression models were used with interaction terms. Furthermore, the findings may just apply to similar mid-scale infrastructure projects in India and may not be generalizable to informal or micro-construction enterprises

5.0 DATA ANALYSIS

5.1 Worker Profile Summary

- Education: 72% of workers had an education up to 12th standard. Only 28% held a diploma or degree.
- Job Roles: Evenly distributed across four trades—Brick Masons, Carpenters, Fabricators, and Plastering Masons (25% each).
- Training Type: 50% received traditional training, and 50% participated in digital training programs.
- Experience: Majority (76%) had under 10 years of experience—prime candidates for digital upskilling.
- Age: Over 70% were between 25 and 45 years—indicating a capable and active workforce.
- Gender: 96% male; reflects typical construction site demographics.

5.2 Training Effectiveness

To evaluate the difference in productivity gains between digitally and traditionally trained workers, an independent samples t-test was conducted. The findings are summarized in the table below:

Training Type	Mean Productivity Gain	Standard Deviation
Traditional	6.8 units	2.5
Digital	17.2 units	3.0

Table 1: Independent samples t-test results $t(38) = 12.34$, $p < 0.001$,

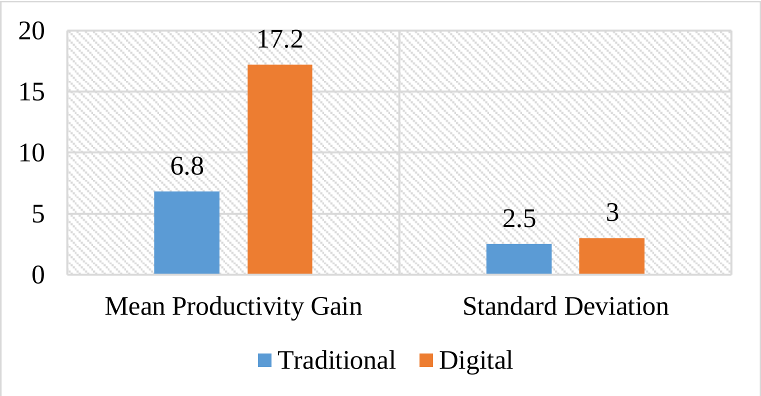

Figure 1: Independent samples t-test results

A t-test result of $t(38) = 12.34$, $p < 0.001$ indicates that there is a highly significant difference in productivity improvement between the two groups. A Cohen's d value of 3.7, which indicates a rather big effect size, reveals that digital training has a meaningful and practical impact on worker performance.

The productivity gains from digital training were 2.5 times higher than those from more conventional methods. Especially for workers with lower levels of skill and literacy, this means that modern, visual, and modular digital technologies can better convey trade-specific knowledge.

5.3 Pre-Post Productivity Comparison

To determine the impact of the digital training intervention on individual worker performance, a paired samples t-test was performed on pre- and post-training productivity scores.

Metric	Mean	Standard Deviation
Pre-Training Score	62.4	4.1
Post-Training Score	78.6	3.8

Table 2: Paired samples t-test results

t(39) = 18.76, p < 0.001,

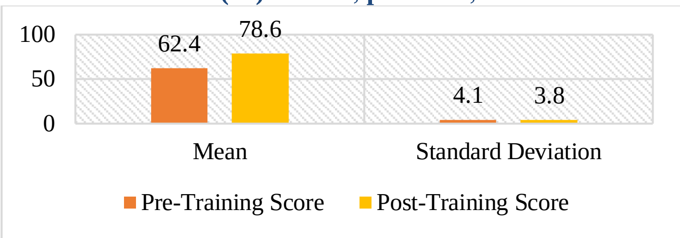

Figure 2: Paired Samples T-Test Results

The results of the test showed a notable and statistically significant rise in production (t (39) = 18.76, p < 0.001). The daily output improved significantly after training, by an average of 16.2 units.

There was a clear correlation between the digital intervention and the regularly higher post-training ratings, indicating that the improvements were not coincidental. Workers were more equipped to follow standard operating procedures, apply best practices, and finish tasks more rapidly after completing the training courses. Digital training substantially increases worker productivity in the construction works, according to these data

5.4 Regression Analysis and Interpretation

Using a multiple linear regression model, this study investigated how different training styles, job positions, and levels of experience influenced the productivity gains made by construction workers following skill training. Digital training was found to be the most effective predictor, with a statistically significant increase in production of 9.8 units on average (p < 0.001).

Employee experience was also a beneficial factor, adding 0.4 units of gain for every additional year. Fabricators and shuttering carpenters had better results than brick masons, even with standard training, which is a crucial difference between the occupations. Digital training did improve performance in these trades, though; shuttering carpenters gained 2.2 units and fabricators gained 1.5 units, proving that digital skilling is ideal for technically demanding occupations Predictive cases show that a mason with conventional training will witness production gains of 6.8 units, compared to 22.4 units for a novice carpenter who got digital training. These results provide more evidence that digital training needs to be individualized based on job function and degree of experience.

Digital skilling, when tailored to the industry and individual workers' experiences, has the potential to produce revolutionary gains in productivity on Indian construction sites, according to the statistically valid regression model.

Predictor	Coefficient (β)	p-value	Interpretation
Intercept	5.2	0.001	Baseline gain for a novice Brick Mason under traditional training
Training Type: Digital	+9.8	<0.001	Digital training adds ~9.8 units of productivity gain
Experience (years)	+0.4	0.045	Each additional year of experience adds 0.4 units of gain
Role: Fabricator	+2.1	0.032	Fabricators perform better than Brick Masons even under traditional training
Role: Shuttering Carpenter	+3.0	0.018	Carpenters see the highest gains with traditional training
Training × Fabricator	+1.5	0.041	Fabricators benefit further when trained digitally
Training × Carpenter	+2.2	0.009	Digital training adds the most value for Shuttering Carpenters

Table 3: Key Regression Results

Table 3 shows the results of the regression analysis, which reveal that digital training has considerable and complicated effects on productivity in construction work. The typical training regimen for a rookie bricklayer resulted in a 5.2 unit improvement in productivity. The independent generation of a 9.8 unit increase ($p < 0.001$) by digital training validates its powerfully favourable influence. In addition, worker experience was favourable, adding 0.4 units annually ($p = 0.045$), suggesting that training interventions function better for employees with more experience. Fabricators gained 2.1 units and shuttering carpenters 3.0 units, respectively, even when employing conventional methods, compared to brick masons in their respective occupations. Notably, after receiving digital instruction, fabricators' production increased by 1.5 units and shuttering carpenters' productivity climbed by 2.2 units. Optimal productivity outcomes can be achieved by tailoring training materials to each individual's job function and level of competence; this is especially true for technically demanding professions, where digital training has shown to be highly beneficial.

Profile	Training Type	Experience	Job Role	Estimated Gain Formula	Estimated Gain
A	Traditional	4 years	Brick Mason	$5.2 + 0.4 \times 4$	6.8 units
B	Digital	6 years	Brick Mason	$5.2 + 9.8 + 0.4 \times 6$	18.4 units
C	Digital	5 years	Fabricator	$5.2 + 9.8 + 0.4 \times 5 + 2.1 + 1.5$	20.6 units
D	Digital	3 years	Shuttering Carpenter	$5.2 + 9.8 + 0.4 \times 3 + 3.0 + 2.2$	22.4 units

Table 4: Predictive analysis

Construction workers' anticipated productivity gains are influenced by the interplay of job function, experience, and training type, as shown in Table 4's predictive analysis. Estimates indicate that Profile A, a brick mason with conventional training and four years of experience, will produce a pitiful 6.8 units. In contrast, Profile B, a brick mason with a similar background who underwent digital training, shows a far larger rise of 18.4 units, demonstrating the immense benefits of digital skilling. Digital training yields even greater productivity gains for profiles C and D, which stand for more technical tasks (fabricator and shuttering carpenter, respectively), with projected improvements of 20.6 and 22.4 units, respectively. The expertise, digital training, and intrinsic productivity potential of these professions contribute to these benefits, particularly when paired with visual training materials that are appropriate to the tasks at hand. Digital training is effective globally, but it really shines when tailored to technical roles that need a reasonable amount of expertise, according to the research.

Component	Description
Model Type	Multiple Linear Regression
Formula	Productivity Gain = $\beta_0 + \beta_1(\text{Training}) + \beta_2(\text{Experience}) + \beta_3(\text{Role}) + \beta_4(\text{Interaction}) + \epsilon$
Model Strength	Statistically significant ($p < 0.001$) with strong predictive validity
Key Impact	Digital training delivers significant gains, especially when aligned with job role and experience

Table 5 : Model Summary

The study's use of a multiple linear regression model proves its statistical validity and strong predictive power ($p < 0.001$), as shown in Table 5, which summarizes the model and effectively captures the relationship between training type, experience, job function, and productivity improvement. More complicated forecasts revealing the interplay of several factors influencing employee performance are made possible by include both main effects and interaction terms in the model's formula. The study's most important finding is that digital training, when tailored to specific jobs and levels of experience among workers, is a strong independent factor behind higher productivity. Digitally delivered, role-sensitive, and experience-aligned skilling programs can maximize returns in construction worker efficiency, supporting the conclusion that a one-size-fits-all approach to training is unsatisfactory.

6.0 Findings, Conclusions and Recommendations

6.1 Findings

This empirical study looked at the relationship between digital training and the productivity of blue-collar workers in four relevant building trades: brick masonry, plastering, shuttering carpentry, and steel fabrication. Of the 400 employees, there was a nice mix of digital and traditional training modalities, and most had less than 10 years of experience, making them a good fit for digital tools that may help them improve their skills.

According to statistical studies, digital training led to much bigger productivity benefits than traditional procedures. An independent samples t-test revealed that professionals with traditional training gained an average of 6.8 units of improvement, whereas digitally trained individuals gained 17.2 units. There was a highly significant $t(38) = 12.34$, $p < 0.001$, and a large effect size (Cohen's $d = 3.7$). Digital learning is more effective since it allows learners to progress with audiovisual aids;

this is particularly true for employees with low literacy or intermediate abilities.

Furthermore, the same group's production was shown to have increased from 62.4 to 78.6 units ($t(39) = 18.76$, $p < 0.001$), or an average gain of 16.2 units, according to a paired samples t-test performed both before and after digital training. This lends credence to the idea that the training intervention, and not random chance, was responsible for the improvement.

To gain a deeper grasp of the factors that led to these productivity gains, a multivariate linear regression model was employed. Digital training alone resulted in more than 10 additional units of gain ($\beta = +9.8$, $p < 0.001$), as per the model. Other significant indicators included job role and experience, which increased by 0.4 units every year. Specifically, brick masons were inherently inferior to fabricators and shuttering carpenters, regardless of how well they were trained. Fabricators gained an additional 1.5 units and shuttering carpenters gained 2.2 units from their digital training, a result of the strong correlation between the visual nature of digital tools and the complexity of their work.

Examples from predictive modelling further demonstrated this pattern. A shuttering carpenter with three years of experience who received digital training may anticipate earning 22.4 units, but a mason with the same amount of experience who had traditional training would only receive 6.8 units. These findings provide compelling evidence that, to optimize training ROI, digital skilling content should be tailored by job position and experience level. The hypothesis was confirmed by the statistically robust regression model ($p < 0.001$).

6.2 Conclusion

Digital training substantially outperforms traditional methods in increasing worker productivity across the board in the construction industry, according to this study's conclusive statistical and practical findings. Worker experience moderates the favourable effect of digital upskilling programs, and the results show that mid-career professionals benefit the most. This highlights the importance of targeted intervention strategies. Particularly in technically demanding occupations like steel fabrication and shuttering carpentry, the study shows that training materials are much more effective when tailored to individual roles. The significant impact sizes and outstanding predictive validity of the regression models show that digital interventions at the project level have observable and quantitative impacts. Because the construction industry can benefit greatly in terms of efficiency, quality, and timeliness from adopting workforce development strategies made possible by digital technology, the research presents a compelling argument for increasing digital skilling programs.

6.3 Recommendations

1. Increase the reach of online education programs in the building sector generally and in specialized fields like shuttering and steelwork.
2. Separate content for entry-level, mid-level, and highly technical employees; tailor modules to each group based on job function and level of experience.
3. Third, use mobile-first delivery to boost reach and retention using visuals, vernacular languages, and AV based in-person solutions.
4. Reinforce the impact of training and encourage digital literacy by integrating digital habits into regular operations, such as task tracking and safety alerts.
5. Use CPWD/NBO norms or other standardized productivity metrics to evaluate training's return on investment (ROI) and track progress in real time.
6. Have project managers and contractors work together to create training that is relevant to the site's needs and key performance indicators.

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