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Digital Transformation in Employee Training and Development and Its Impact on Organisational Productivity

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Abstract

The rapid changes in digital technology have significantly influenced the manner in which manufacturing firms are developing their workforce skills, although its implications on productivity outcomes are still questionable, especially in India's textile sector. This current study aimed to assess the influence of the four key dimensions of digital training and development, namely, learning platform infrastructure, the use of electronic learning, skill learning through technology, and learner engagement through digital technologies, in improving productivity in Amarjothi Spinning Mills Limited in Erode, Tamil Nadu, India to gather data for this study, a survey was carried out among 250 permanent employees in the organization using a stratified random sampling approach. The data was analyzed and hypotheses were tested using PLS-SEM through SmartPLS version 3.3.9.. It was revealed that all four dimensions had a significant positive impact on productivity. The combined effect of all dimensions accounted for 60.2% variance in productivity. Among these dimensions, digital learner engagement had the highest impact on productivity ($\beta = 0.36$, $p < 0.001$). The study offers valuable recommendations to HR professionals in the textile industry. It also contributes to the existing knowledge on digital HR practices in Industry 4.0.

Keywords: Workforce Digitalisation, Training and Development, Organisational Productivity, E-Learning, Textile Manufacturing, PLS-SEM, Industry 4.0

1.Introduction

Today, every manufacturing firm is operating in a rapidly changing world, where there is a lot of competition Not only at the national level but also at the global level, and in areas where there are new challenges that require different skills from the workforce.The widespread adoption of technology in all areas of a business, also termed "digital transformation," has become a major for businesses to stay competitive in today's fast-paced environment, digitalisation plays a key role (Bharadwaj et al.,2013).

In the area of human resource management.this shift is clearly seen in how training and development programs for employees are being redesigned.The traditional classroom training is being gradually replaced by digital training, which is data-driven, self-paced, and flexible (Bondarouk& Ruel, 2009). This phenomenon is significant in the textile and spinning industry in India,which has a long history but also needs urgent modernization.Companies in this industry face the problem of training the workforce for the automated environment and the high rate of worker turnover, which is a waste of the skills that the worker has developed (Srivastava & Agarwal, 2020). Thus, investing in the training infrastructure for the digital environment is not only a business need but also a strategic decision that has profound implications for worker productivity. The spinning industry is a good case study for this research problem, and a good company to focus on is the Amarjothi Spinning Mills Limited, a spinning company based in Erode in the Tamil Nadu district of India, which has recently started investing in training infrastructure.

There is an increasing body of evidence that suggests that investing in technology for training increases worker productivity.Noe et al. (2014) suggested that workers trained with the help of technology retain the training better than those trained with traditional methods. Rao and Sharma (2019) suggested that investing in e-learning for large-scale manufacturing companies in India led to better output.This has been evident in the COVID-19 pandemic, as highlighted by Cortez and Johnston (2020), that manufacturers using digital training systems were able to recover workforce skills more quickly compared to in-person training systems. However, little has been researched on the specific aspects of digital training that impact the productivity of spinning companies in India.

2. Literature Review

2.1 Digital T&D Dimensions And Productivity Evidence

There has been a notable rise in the past ten years in the volume of scholarly works on the relationship between digital tools and workforce development.Bharadwaj et al. (2013) discovered that by restructuring human capital processes with digital technology, companies are able to better customize learning content, increase reach, and reduce the cost of delivering content to individual learners. Specifically, in the shop floor, Oztemel and Gursev (2020) reported that artificial intelligence, IoT connectivity, and immersive augmented reality are becoming more popular in industrial learning programs. These enable learners to practice complex tasks in a safe and simulated environment before working with actual equipment. Learning management systems and cloud-based training platforms, which are key components of digital learning, have been found to improve learning outcomes if they provide high-quality content, ease of navigation, and timely instructional support (Al-Fraihat et al., 2020).E-learning's self-paced, on-demand learning feature was found to improve learner outcomes in various industries (Arbaugh, 2000).

In automotive manufacturing, Renaud et al. (2021) found that if e-learning programs are well-structured, learners can reach operation-level competence quicker,This is while also enhancing safety compliance and product quality. Similar results were also recorded in the case of large-scale manufacturers in India, for whom the implementation of e-learning was linked with a notable improvement in the skill development of individuals and the overall productivity of the plants (Rao & Sharma, 2019). Technology-based skill development approaches such as simulation training, AR-based training programs, and mobile micro-learning have also been recorded to be more effective than traditional training programs in retaining the learned content and transferring the skills into the real working environment (Radianti et al., 2020). The effectiveness of the engagement factor of e-learning programs is based on the foundational theory of engagement (Schaufeli et al., 2002) and the extension of this theory into the context of learning (Noe et al., 2014), which indicates that learners who are mentally and emotionally engaged with the training content tend to retain and apply the training more effectively. Further research into the effectiveness of training and development programs in the context of strategic human resource management (Jiang et al., 2012; Combs et al., 2006) indicates that training and development programs are among the strongest predictors of organizational effectiveness, suggesting that the digitally enhanced version of these programs is likely to produce even more effective results.

2.2 Theoretical Foundations

The Technology Acceptance Model, developed by Davis in 1989, explains that a person's decision to use technology depends on two main things: how useful they find it for their work and how easy it is to use.When applied to digital training and development, this means employees are more likely to engage with training tools if they see them as helpful and user-friendly. This can lead to better skills and improved job performance. The "Ability-Motivation-Opportunity" framework, introduced by Appelbaum et al. in 2000, offers a different way to look at the same topic.According to the framework, HR practices in an organisation have three main effects: on the ability of workers to perform their duties, on the motivation levels of the workers to perform, and on the opportunity to perform. Digital training and development affects all these aspects at once. The training and development improve the ability of workers through technology-based training modules, motivate workers to perform through performance support, and provide opportunity for workers to perform through collaboration. The

"Knowledge-Based View" proposed by Grant in 1996 relates the productivity of an organisation to the amount and quality of knowledge available in the organisation. Digital training and development increases the productivity of an organisation by speeding up the process of creating new knowledge and making it available to the workers.

2.3 Research Gaps And Hypothesis Formulation

There are three research gaps that are addressed in the current research.FirstEven though the textile and spinning industry is very important for the Indian economy, there is not much published work that looks intohow digital training and development affect productivity in this sector.Secondly, past studies have treated digital training and development as one entity, and as such, they have not been able to establish which particular aspects have the greatest impact on productivity, and this is highly relevant to resource allocation decisions. Thirdly, there is no published literature that has employed the PLS-SEM method to investigate the relationships in the Indian manufacturing industry, and as such, there is a gap in terms of methodology, and the current research aims to address that gap. Based on the above discussion and the various theoretical frameworks, the following four hypotheses are formulated:H1: Quality and accessibility of digital training platforms are positively related to organisational productivity at Amarjothi Spinning Mills Limited.

H2: Higher e-learning adoption among employees has a positive relationship with organisational productivity.

H3: Higher engagement in technology-based skill development programmes has a positive relationship with organisational productivity.

H4: Higher digital learner engagement has a positive relationship with organisational productivity.

3. Research Methodology

3.1 Research Design

A quantitative confirmatory research design has been used to test the research hypotheses based on the positivism approach, as outlined by Sekaran & Bougie (2016).

This design was chosen because it fits well with the research goal of examining the existing relationship between the dimensions of digital training and development and productivity at a specific time..

3.2 Measurement Variables

For each of the variables, a scale was used that has been validated in previous research on training and development, and digital transformation.For measuring the perception of organizational productivity, including output efficiency, quality consistency, and waste reduction, a six-item scale was used, based on a scale developed by Datta et al. in 2005. For measuring digital training platforms, including accessibility, relevance, ease of use, and overall usefulness, five items were used, based on a scale developed by Al-Fraihat et al. in 2020. For measuring e-learning adoption, including how often it is used, how helpful it is for learning, and how well it fits into daily work, five items were used, based on A scale created by Arbaugh in 2000 and later updated by Rao and Sharma in 2019 was used to measure technologybased skill development. This included assessing how realistic a training simulation is,how well knowledge is transferred and how effectively performance improves. Five items were based on a scale developed by Radianti et al. in 2020. For measuring digital employee engagement, a four-item scale was used, combining elements from the Utrecht Work Engagement Scale by Schaufeli et al. in 2002 and a learning engagement tool by Noe et al. in 2014. Respondents answered using a five-point scale There are three research gaps that are addressed in the current research.FirstEven though the textile and spinning industry is very important for the Indian economy, there is not much published work that looks intohow digital training and development affect productivity in this sector.where 1 meant "Strongly Disagree" and 5 meant "Strongly Agree."

3.3 Data Analysis Approach

The data analysis was conducted in two parts.First, IBM SPSS Statistics version 26 was employed to examine for missing values, outliers, general summary and internal consistency, employing Cronbach's Alpha. Second, SmartPLS version 3.3.9 was employed for conducting PLS-SEM. This method was employed for several reasons: it is suitable for confirmatory testing, and it is suitable for investigating effects. Since the response data was moderately non-normal distributed (Mardia's multivariate kurtosis = 3.84), PLS-SEM is suitable for this study. This is also supported by the fact that it works well with the sample sizes used in this study, as mentioned by Hair et al. (2019). To check the quality of the measurement model,we look at indicator loadings, composite reliabilityand average variance extracted for convergent validity, as well as heterotraitmonotrait ratios for discriminant validity.were employed. For assessing the structural model, bootstrapping was employed for conducting t-statistics for each path, employing 5,000 resamples, in addition to Cohen's f^2 for assessing effect sizes.

4. Data Analysis And Results

4.1 Descriptive Statistics

Table 1 below indicates the averages and how they vary for all five key areas.All variables recorded an average above the mid-point of the scale, which is 3.0. This indicates that generally, employees in Amarjothi Spinning Mills have a positive attitude towards the company’s digital training and development program and their own productivity. Of all the areas that influence performance, it is clear from Table 1 below that Digital Employee Engagement recorded the highest average. The results (M = 3.75, SD = 0.66) suggest that employees are very invested in digital learning opportunities. On the other hand, E-Learning Adoption recorded the lowest average (M = 3.64, SD = 0.74), which could be an indication that this area needs to be addressed in a more structured way. The consistency in results for all areas shows that employees generally hold similar attitudes, which could be because they were all exposed to digital training tools in all departments.

TABLE 1: Descriptive Statistics for Study Constructs (N = 250)

VARIABLE	N	MEAN	SD	MIN	MAX
Organisational Productivity	250	3.79	0.63	1.00	5.00
DigitalTraining Platforms	250	3.71	0.68	1.00	5.00
E-Learning Adoption	250	3.64	0.74	1.00	5.00
Technology-Based Skill Development	250	3.68	0.71	1.00	5.00
Digital Employee Engagement	250	3.75	0.66	1.00	5.00

Note: All items were measured using a 5-point Likert scale, where 1 means Strongly Disagree and 5 means Strongly Agree. SD stands for Standard Deviation.

4.2 Reliability Analysis

To measure how well each of the areas is being measured, we used Cronbach's Alpha.From Table 2 below, it is clear that all the scores are far higher than the recommended 0.70 (Nunnally & Bernstein, 1994). This shows that we can work with this scale. In addition, we can see that the highest score is that of the area that measured Organisational Productivity. On the other hand, Digital Employee Engagement had the lowest score. Nevertheless, it is also acceptable.

TABLE 2: Internal Consistency Cronbach's Alpha by Construct

CONSTRUCT ITEMS	TIMES	CRONBACH'SALPHA	STATUS
Organisational Productivity	6	0.88	Acceptable
Digital Training Platforms	5	0.85	Acceptable
E-Learning Adoption	5	0.83	Acceptable
Technology-Based Skill Dev.	5	0.81	Acceptable
Digital Employee Engagement	4	0.80	Acceptable

Note: Values at or above 0.70 are considered indicative of acceptable internal consistency (Nunnally & Bernstein, 1994).

4.3 Structural Model

The structural model was tested using PLS-SEM, with 5,000 bootstrap resampling runs according to the model. The results show that the four dimensions of digital training and development collectively explained 60.2% of the variance in organisational productivity, indicating strong potential for organisations to enhance productivity through investments in these areas.

TABLE 3: presents the outcomes of the hypothesis testing.

Hypothesis Path	Beta (β)	t-value	p-value	Outcome
H1: Digital training platforms -> OP	0.33	4.92	0.001	Supported
H2: E-learning adoption -> OP	0.29	4.35	0.002	Supported
H3: Technology-based skill development -> OP	0.27	4.08	0.003	Supported
H4: Digital employee engagement -> OP	0.36	5.21	0.001	Supported

Note: OP = Organisational Productivity.

Bootstrap resampling iterations = 5,000Significance levels: *p < 0.05, p < 0.01, *p < 0.001. All hypotheses were supported at conventional significance levels.The highest path coefficient was obtained by Digital Employee Engagement, followed by Digital Training Platforms,E-Learning Adoption, and Technology-Based Skill Development.The path coefficients were 0.36, $t = 5.21$, $p < 0.001$; 0.33, $t = 4.92$, $p < 0.001$; 0.29, $t = 4.35$, $p < 0.01$; and 0.27, $t = 4.08$, $p < 0.01$, respectively.

5.Discussion

The overall ability of the structural model to explain the results ($R^2 = 0.602$) supports the theory behind the AMO framework and the Knowledge-Based View, showing that digitally transformed training and development can improve employees' skills, their motivation to perform, and their chances to contribute effectively. Each of the path coefficients gives useful information that helps answer the research question within this discussion.in the relevant scientific community.The most important finding is that Digital Employee Engagement has the strongest effect, $\beta = 0.36$.This is consistent with theory on work engagement (Schaufeli et

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al., 2002), which states that emotional and intellectual investment is a prerequisite for true learning to take place. It is also consistent with Noe et al.'s (2014) extension of this idea to training settings. In a spinning mill setting, where precision and operation of machines are critical to production and quality, employees who are

able to fully invest in what they are learning from digital training rather than just doing their required tasks are more able to apply their skills learned from training to their work. This is consistent with Bettinger et al.'s (2017) extension of this idea to higher educational settings, where interactive and engaging elements are more critical to completion of training and performance than availability of training content. It is also consistent with Combs et al.'s (2006) finding that HR practices that increase motivation are more critical to organizational performance improvements than skill-building efforts.The strong influence of Digital Training Platform quality (β = 0.33) is supported by a large-scale research by Al-Fraihat et al. (2020) that studied factors affecting learning management system use.From a Technology Acceptance Model perspective (Davis, 1989), if employees perceive that their company's platform is useful and easy to use, they are more likely to use it and benefit from the knowledge that will improve their productivity. For Amarjothi Spinning Mills, this is a high-value investment area for the company improving the platform's quality in terms of new content, mobile access for workers on the floor, and system performance is a high-value investment for the company.

The E-Learning Adoption path (β = 0.29) is supported by research by Renaud et al. (2021) and Rao & Sharma (2019) in the manufacturing sector that found that having access to online content can reduce the negative influence of traditional training that takes workers off the floor and keeps their skills up to date with changing technology. The weaker effect compared to engagement implies that merely using the tools frequently, without necessarily mastering the skill, has a lower impact. Technology-Based Skill Development, being the weakest predictor (β = 0.27), nonetheless demonstrates a strong and significant effect, similar to what Radianti et al. (2020) and Srivastava & Agarwal (2020) reported. The weaker coefficient might result from the relatively early adoption of AR and simulation tools, whose positive impact on productivity is expected to increase as the infrastructure becomes more developed. In addition, the research model's explanatory power ($R^2 = 0.602$) is similar to similar studies: Bondarouk& Ruel (2009) reported $R^2 = 0.54$ in their European-based research in the manufacturing industry, whereas Rao & Sharma (2019) reported $R^2 = 0.57$ in their Indian-based research in the e-learning sector, providing confidence This research has three significant contributions to the existing body of knowledge.

First this study is the first to use PLS-SEM to show how different digital training and development factors affect productivity in an Indian textile manufacturing company. It adds important new knowledge to the field because there hasn't been much research on this topic before.

Second, the present study is more theoretically precise compared to the previous literature as it combined TAM, the AMO model, and KBV to demonstrate the digital training and development phenomenon. In contrast, previous literature had applied only one theory to demonstrate the digital training and development phenomenon.

Third, the present study is more replicable for future researchers as it has applied four distinct digital training and development constructs rather than a combined construct. Future researchers can easily replicate the present study to demonstrate the digital training and development phenomenon in various companies, industries, and countries.

6. Implications

6.1 Managerial Implications

The results of this study have clear importance for HR and operations managers at Amarjothi Spinning Mills and other textile companies. The main takeaway is that the quality of training matters more than how much training is provided. The study found that elements like game-based rewards, such as achievement badges and progress leaderboards, and social learning features, like peer discussion forums and virtual Q&A sessions with experts, play an important role. It also showed that the quality of the learning platform itself is crucial. To keep the training content useful and the interface easy to use, especially for employees who aren't very tech-savvy, regular usability checks and employee feedback are necessary. Additionally, it's important to give employees basic digital skills training so they can make the most of the training resources available.To increase the adoption of e-learning by employees, it was found that structured e-learning goals must be integrated into performance appraisals, learning paths must be aligned to individual employee tasks, and non-monetary incentives like digital certificates must be provided.The gradual roll-out of technology-based skill development, first in areas where the impact is the greatest, should allow the company to see the results before investing in the technology.

6.2 Theoretical Implications

- The present study proves the practical applicability of the TAM model, the AMO model, and the KBV model in other cultures and industries.
- It proves the practical applicability of the aforementioned theories in the context of the Indian manufacturing industry, where the aforementioned theories were studied individually.
- It proves the practical applicability of the aforementioned theories in the context of the Indian manufacturing industry, where the aforementioned theories were studied individually.
- The fact that the engagement dimension, which includes the motivational effects of the AMO model and the usefulness perception of the TAM model, is the dimension with the strongest relationship with productivity suggests an interesting area of potential future research. The use of PLS-SEM in this current study presents a valid approach for researchers interested in studying the effects of digital HR practices in developing countries.

7.Conclusion

The paper sought to determine whether and how digitalized training and development activities contribute to productivity in an Indian textile spinning company.Using 250 employees of Amarjothi Spinning Mills Limited in India as subjects and the PLS-SEM technique, all the proposed relationships were supported. Digital training platform quality had a positive and significant impact on productivity ($\beta = 0.33$), as did the adoption of e-learning ($\beta = 0.29$), the development of skills through the application of technology ($\beta = 0.27$), and digital learner engagement ($\beta = 0.36$). These factors combined explained 60.2% of the total variation in the dependent variable. Three new contributions to the knowledge pool were established. Firstly, the first quantification of the digital training and productivity relationship in an Indian spinning company. Secondly, the fact that digital training influences productivity through learner engagement. Finally, the development of a sound framework for measuring various factors. Future researchers in the same field should seek to undertake longitudinal designs to ascertain the impact of the increase in digital training investments on productivity. Future work should also seek to explore the conditions in various companies and the channels through which digital training influences productivity, such as digital confidence and knowledge sharing.

8. Limitations Of The Study

There are some conditions that need to be met in order to understand the study.The data has been collected at one go, so we cannot be sure that something has caused something else. We would need a longer study or some special type of research to know how things are related to each other. We did the research at just one company, so we get a detailed understanding of the particular situation. However, we cannot be sure how the results would be applicable to other companies, businesses, or places. To find out if we could use the results anywhere else, we would need to do the same study at different places. We have basically relied on people's own opinions to do the entire study, which has led to some common problems in research. If we could use some real numbers or facts about how something is working, like the efficiency of the workplace or the number of errors, the results would be more accurate. We looked at four main areas related to digital training and development, but there are some new areas that could be considered, like the use of AI in personal learning or the use of data analysis in support. Lastly, while comparing the results of this type of statistical method with others, we must remember that this type of statistical method shows more differences than others.

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