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Digital Technology Adoption and Employee Productivity in Real Estate Firms: Mediating and Moderating Effects of Technological Drivers, Barriers, and Operational Knowledge in North-Central Nigeria

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Abstract
The need for the adoption of digital technology is becoming increasingly important for the improvement of the efficiency of operations and employee productivity in the real estate sector. This study explores the effect of the availability of digital technology, employee knowledge of digitalization, and the use of technology on employee productivity in the real estate sector in North-Central Nigeria. It further explores the mediation role of technological drivers and technological barriers, and the moderating role of employees' working knowledge of the effect of the use and availability of technology on employee productivity. A quantitative research design and methodology were used for this study, and data were collected through structured questionnaires among some real estate businesses' employees in the states included in North-Central Nigeria, namely Abuja, Benue, Kogi, Kwara, Nasarawa, Niger, and Plateau States. Through partial least squares structural equation model analysis (PLS-SEM), the proposed hypotheses were rigorously tested in this study. Results showed that both the use of available digital technology and employees' know-how of digitalization significantly impact the use of technology and employee productivity positively and negatively, respectively. Technological drivers served as positive mediators, but technological barriers negatively mediate the impact of available technology on employee productivity. Employee working knowledge positively moderated the positiveness of technological use on employee productivity for improved real estate industry performance and recommends formal employee continuous education and technological infrastructure in the industry for increased employee productivity and other beneficial values offered by adequate technological use within the industry.

Keywords: Digital Technology, Employee Productivity, Real Estate Firms, Technological Drivers, Technological Barriers, Operational Knowledge, North-Central Nigeria

1. Introduction

Digital transformation has emerged as a key enabler of increased competitiveness and effectiveness in the present knowledge-based economy. Within the real estate industry, the use of sophisticated tools such as Building Information Modelling (BIM), Geographic Information Systems (GIS), Customer Relationship Management tools, web marketing platforms, and electronic document management tools is currently changing the dimensions of business operations, workflow management, and delivery of services in the industry (Fengchen, 2023; Rabby, Chimhundu, & Hassan, 2022). However, the impact level of these tools being available, used, and implemented for achieving improvement in employee productivity outcomes is currently inadequately established, especially within the emerging economy of Nigeria.

North Central, Nigeria, is one of the areas where a real estate firm can establish itself in a truly unique operating environment with infrastructure issues, inconsistent use of technology, and large disparities among employees with regard to use and understanding of Information and Communication Technologies. While evidence from previous research indicates a positive boost in efficiency levels, innovativeness, and overall performance within an organization brought about by technological advancements, much is left unexamined concerning the specific impact relationships between infrastructure access, workers' technological understanding, and technological utilization levels and performance outcomes (Bakari et al., 2023; Oyetunji, 2023). It is, therefore, significant to understand the role of technological drivers and inhibitory factors in influencing these relationships, with moderating effects brought about by employees' working-level technological understanding of those uses within the real estate operating environment, with evidence beneficial in facilitating a positive technological adoption process within the field of real estate operations (Asibi, Ojokuku, & Udoh, 2023; Dada & Ogunode, 2025).

2. Literature Review

Digital Technology and Employee Productivity

Digital technologies increase efficiency in communication, automation, and data management, ultimately leading to an increase in the productivity of employees within the real estate industry. Optimized use of technology helps save time on tasks, reduces mistakes, and promotes innovation, leaving employees with enough time for priority tasks.

Cloud computing platforms and collaboration platforms like Teams and Zoom foster effective communication, idea sharing, and remote work, thus increasing efficiency, job satisfaction, and organizational commitment. Therefore, Nwankpa & Roumani, 2024; Khalil Marat, 2023; Nurwidyani et al., 2024, argue that information technology offers performance tracking and immediate feedback, hence motivation and performance in an organization as by Yoma et al., 2025.

Digitalization helps both customers' service support and enhance working efficiency via online platforms, reducing costs and increasing responsiveness rates (Attaran, Attaran, & Kirkland, 2019; Halik, Lintang, & Patandean, 2024). In a totally connected and updated technological working environment, there are quite a few challenges that may take place, such as the influence of technostress, burnout, and reduced employee productivity because of continuous technological advancement (Supriyadi et al., 2025; Harahap et al., 2023). Over-reliability on virtual communication may affect teamwork and continuous exposure to screens can trigger employees' health concerns about their performance outputs (Gamede, Mtotywa, 2022; Khalil Mar

Productivity relies heavily on competency and support for employees within an organization. Competent employees who can exploit the capabilities of these technologies fully will increase not only the level of output but also innovation within the organization. Thus, according to Haramija & Fruk, 2022; Al-kharabsheh et al., 2022; Syamsulbahri & Bardai, 2025, real estate businesses that embrace cloud computing, integration, and optimization have easily improved their level of efficiency and competitiveness within the industry. Gala, Bandaso, & Sambara, 2025; Angioha et al., 2020 support technological advancement as improving the level of productivity within real estate businesses by streamlining operations, facilitating cooperation, and creating possibilities to innovate.

Technological Drivers and Barriers

Support from the organization, commitment from the management, and infrastructure support are some technological drivers that drive the use of technology in organizations. Such drivers help employees conduct work efficiently with the help of technology and also increase the effectiveness of the workflow of an organization. Support from management enables employees to adapt new technologies, leading to increased efficiency and effectiveness within an organization. However, some factors such as cost of implementation, lack of acceptance, lack of training, and complexity may serve as inhibiting forces within an organization for a smooth integration of digital technology. Fear, lack of technical knowhow, and lack of adequate training can limit the benefits derived from technology investment. Moreover, big businesses with a wide geographic reach may encounter difficulties in implementing technologies, including digital technology, due to these complexities (Stentoft et al., 2021).

Innovation management emphasizes the importance of both drivers and constraints coming into play. Though most organizations excel in coming up with ideas, the problem lies in those ideas being evaluated, ranked, and turned into reality (Gruenhagen, Cox, and Parker, 2022). Technology can be used in your favor in order to reduce constraints by providing tools such as collaboration platforms, engaging platforms for innovating and choosing ideas, among others (Alam et al., 2025; Rovshan, 2024).

Technological drivers make effective technological adoption and innovation achievable, while some technological and humanistic barriers may prevent the increased levels of productivity and performance ensured by these technologies. For an organization to digitally transform successfully, technological drivers must be harnessed, and the related technological and humanistic barriers must be minimized for employees' productivity and an organization's competitiveness

(Diawati et al., 2023; Anakpo, Nqwayibana & Mishi, 2023).

Operational Knowledge as a Moderator

Employee-operational knowhow is very important because it includes employees' technical skills, technological literacy, and awareness about business processes. When employee-operational knowhow is high, employees will be able to handle technical problems, streamline work procedures, and use new technologies, which will increase efficiency and employee productivity (Alam, Zhang, and Shehzad, 2023; Taghizadeh et al., 2021).

Operational knowledge is also a moderating factor in the relation between the utilization of technology and employee productivity. Even with technology in use, the impact of such technology on performance can only be ensured if employees can use it properly (Xie et al., 2021; Hussain et al., 2022). It is only those organizations who emphasize developing employee skills in a manner where continuous training and sharing of knowledge can produce a multiplier effect in terms of increased performance due to technological advancements in the organization (Khalaf & El Mokadem, 2025).

Theoretical Foundation

Technology–Organization–Environment (TOE) Framework

The Technology-Organization-Environment (TOE) model is a comprehensive tool for understanding the contexts underpinning technological acceptance in an organization. It underlines the fact that technology acceptance is carried out within three dynamic contexts. The technological context takes into consideration the availability, accessibility, and adoptability of technology, which is directly relevant when investigating the use of digital technology within the real estate industry (Lin and Chen, 2023; Malik et al., 2021). The next is the organizational environment, which takes into consideration factors such as support, infrastructure, and capabilities within an organization, and these greatly impact the effectiveness of technological integration within those mentioned environments (Ng, Lit, and Cheung, 2022; Chittipaka et al., 2023). The third is the environmental context, which focuses on the impact of external forces of competition, legislation, and market demands that may impact technology acceptance positively or negatively within a given industry (Nguyen, Le, and Vu, 2022; Al-Hadwer et al., 2021). From a different standpoint, the use of the TOE model helps understand both the capabilities within an organization and the external factors influencing the use of digital technology within the real estate industry, which directly affects employee productivity within an organization (Kumar and Shankar, 2024).

Technology Acceptance Model (TAM)

TAM is concerned with individual-level characteristics explaining technology acceptance. It is proposed that employees' use of technology is affected mostly by perceived usefulness, defined as an employee's belief in technology-enhanced job performance, and perceived ease of use, defined as an employee's belief about technology use with little difficulty of use (Davis, 1989; Silva, 2015). For my assignment, TAM helps describe employees' levels of awareness, skills, and attitudes about the use of technology influencing employees' actual use of technology in the workforce (Marangunić & Granić, 2015; Venkatesh et al., 2003). With the use of both TAM and TOE, an understanding from a macro level and a micro level is used in creating a full understanding related to advances in the use of technology and increased productivity within realty businesses (Musa et al., 2024; Al-Adwan et al., 2023).

3. Methodology

For the proposed research, a quantitative approach in research design was used to analyse the impact of digital technology on employee productivity within registered real estate agencies in North-Central Nigeria. Structured questionnaires were used to gather data from 320 employee volunteers. A five-point Likert scale was used in the measurement of key study constructs such as the use of technology, awareness, use, drivers, and barriers of technology, and employee productivity. A partial least squares structural equation model analysis in SmartPLS 4.0 software tools was used to estimate both the structural and measurement models. The study used a series of tests in order to establish the aspects of reliability and validity, including both composite reliability and average variance extracted for the proposed study.

Structural Equation Modelling (SEM)

Structural Equation Modelling It is a multivariate analysis methodology classified under the group of 'Second Generation Multivariate Analysis Techniques' because it investigates intricate relationships among latent variables by simultaneously embodying 'Confirmatory Factor Analysis,' 'Path Analysis,' and

'Multiple Regression Analysis.' It is increasingly being used since its advent in marketing research in the 1980s (Thakkar, 2020; Owolabi, Ayandele, & Olaoye, 2020). For this research, the variance-based form of SEM, Partial Least Squares Structural Equation Modelling (PLS-SEM) was selected because it would help measure the impact of 'Key Dimensions of Digital Technologies,' 'Availability,' 'Knowledge,' 'Utilization,' 'Drivers,' and 'Challenges' related to employees' 'Productivity' in the real estate industry. This would be a suitable choice because the proposed research is exploratory in scope, has intricate 'Latent Variables,' and relies on a methodology because of which 'reflective' and 'Formative Models' with 'non-Normal Data Distribution' can be taken care of with a 'Moderate Sample Size' (Hidayat & Wulandari, 2022; Barrett, 2007).

Questionnaire Administration

Based on the observations gained from the pilot study, the proposed questionnaire was refined, and the final version was subsequently carried out among the employees of registered real estate businesses in the North-Central region of Nigeria. A total of 320 questionnaires were given out for the proposed study among the targeted respondents. Of these, 287 were recovered, giving an effective response rate of 89.7%. After subjecting the retrieved data to scrutiny for eliminating both invalid and outlier observations, 271 questionnaires were found valid, accounting for 84.7% of the total questionnaires retrieved.

Table 1: Questionnaire administration

SN	Description	Number and Percentage
1	Questionnaire administered	320
2	Questionnaire retrieved	287 (89.7%)
3	Questionnaire used for analyses	271 (84.7%)

Demographic Attributes

This study collected demographic information from its respondents. Frequency and percentage analyses were performed to explore the profiles of its respondents. The results are represented below in Table 2.

Table 2: Demographic data of respondents

S/N	Questions	Options	Frequency	Percentage (%)
1	Gender	Male	186	85.3
		Female	32	14.7
2	Educational Qualification	Certificate/ND	21	9.6
		Degree/HND	130	59.6
		Master's/PGD	56	25.7
		PhD	11	5.0
3	Professional Qualification	Probationer	66	30.3
		FNIVS	66	30.3
		ANIVS	92	42.2
4	Years of Experience	Less than 5 years	68	31.2
		5–10 years	85	39.0
		Above 10 years	65	29.8

Demographic data from the respondents, as presented in Table 2, outline the four important variables of gender, educational qualification, professional qualification, and years of experience. The findings indicate that the sample is dominated by males, which account for 85.3 percent, while females represent only 14.7 percent. This clearly reflects the continuous male domination within the real estate practice in the study area. On educational background, the majority of the respondents have a degree or HND qualification, taking 59.6 percent of the sample. The second most ranking comprises those holding a Master's degree or PGD at 25.7 percent. 9.6 percent of the respondents reported having Certificate/ND qualifications, whereas PhD holders represent the least with 5.0 percent. These figures indicate that the majority of the practitioners have attained appreciable tertiary education, which is consistent with the academic requirements for professional practice in the estate surveying and valuing profession. Results on professional qualification reveal that the members of ANIVS form the largest category, at 42.2 percent, demonstrating a strong proportion of fully registered professionals. Probationers take 30.3 percent, while FNIVS holders also make up 30.3 percent. This distribution reflects a diverse mix of practitioners at different phases of professional development within NIESV and enhances the representativeness of the sample. By years in practice, the highest proportion falls within 5-10 years of practice at 39.0 percent, showing there is great midcareer presence within the profession. It is followed by those with less than 5 years of experience at 31.2

percent, meaning there is still continued entry into the ranks by younger professionals. At the same time, persons who have more than 10 years of experience are 29.8 percent, adding depth and expertise to the population surveyed. Generally, it depicts a balance of early-career, middle-level, and senior professionals across the study area.

4. Results and Discussion

Reliability Assessment of PLS-SEM Analysis

In PLS-SEM, reliability assessment is very important since the reflective items in the measurement model are to show stable and consistent results for observations. According to Yusif et al. (2020) and Dolinting & Pang (2022), reliability reveals the level at which the measurement scale is free from random error, while consistently capturing the intended construct. Though most scholars state that both Cronbach's alpha and composite reliability are frequently used in reporting, composite reliability is identified as the more appropriate option in PLS-SEM. Therefore, Li & Lay (2024), Canatay et al. (2022), Purwanto & Sudargini (2021), and Mukhtar, Kamin & Saud (2022) recommended the reporting of both in order to cover the assessments comprehensively. On the other hand, the ρc value exceeding 0.7 indicated that the reflective construct was reliable according to Haji-Othman and Yusuff, 2022. However, Ghasemy et al., 2020; Amatan, Han & Pang, 2025 and Li & Lay, 2024 have elaborated that the composite reliability of 0.6 was acceptable in newly developed scales. Table 3 presents the reliability statistics of all constructs in the present study.

Table 3: Reliability Assessment of Constructs

Construct	Cronbach's Alpha	rho_A	Composite Reliability (ρc)	Average Variance Extracted (AVE)
Digital Technology Availability	0.965	0.966	0.970	0.802
Employees' Digitalization	0.942	0.944	0.954	0.776
Employee Productivity	0.878	0.978	0.911	0.720
Operational Knowledge	0.918	0.849	0.914	0.642
Technological Barriers	0.899	0.902	0.930	0.768
Technological Drivers	0.948	0.949	0.958	0.793
Technology Utilization	0.944	0.945	0.956	0.782

Specifically, the results indicated that all constructs had composite reliability values that fell between 0.914 and 0.970, therefore meeting the threshold of 0.7. The Cronbach's alpha values were also between 0.878 and 0.965, reflecting acceptable internal consistency for each construct. The values of rho_A were also satisfactory, lying between 0.849 and 0.978. Overall, the measurement model reflects adequate reliability, suggesting that the measures are consistently associated with each other and thus will be suitable for further analysis in the structural model.

Evaluation of the Structural Model

The assessment of the structural (inner) model is the second step in the PLS-SEM assessment procedure. During this step, the structural model defines the causal relationships between latent constructs. Moreover, it forms the basis for testing the study hypotheses and answering the research questions. In general, the assessment of the structural model is the process applied to evaluate its predictive capability regarding the endogenous constructs.

Following established PLS-SEM guidelines, the assessment is performed based on several key criteria of Dolinting & Pang, 2022; Li & Lay, 2024; Canatay et al., 2022. The significance of the path coefficients is assessed through the bootstrapping procedure, showing the strength of the hypothesized relationships and their relevance. The model's explanatory power is assessed through the coefficient of determination (R^2), showing the proportion of variance in each endogenous variable explained by its predictors. The effect sizes are computed to determine the magnitude of each exogenous variable's influence on the respective endogenous constructs. Predictive relevance obtained through cross-validated redundancy provides a basis for assessing the model's capability to predict observed values. Besides that, the global goodness of fit index has been employed to provide the overall assessment of model fit. In total, these evaluation criteria guarantee that the structural model will be robust and reliable in terms of explaining and predicting the set of relationships within the conceptual framework proposed by Purwanto & Sudargini (2021); Mukhtar, Kamin & Saud (2022); Haji-Othman & Yusuff (2022).

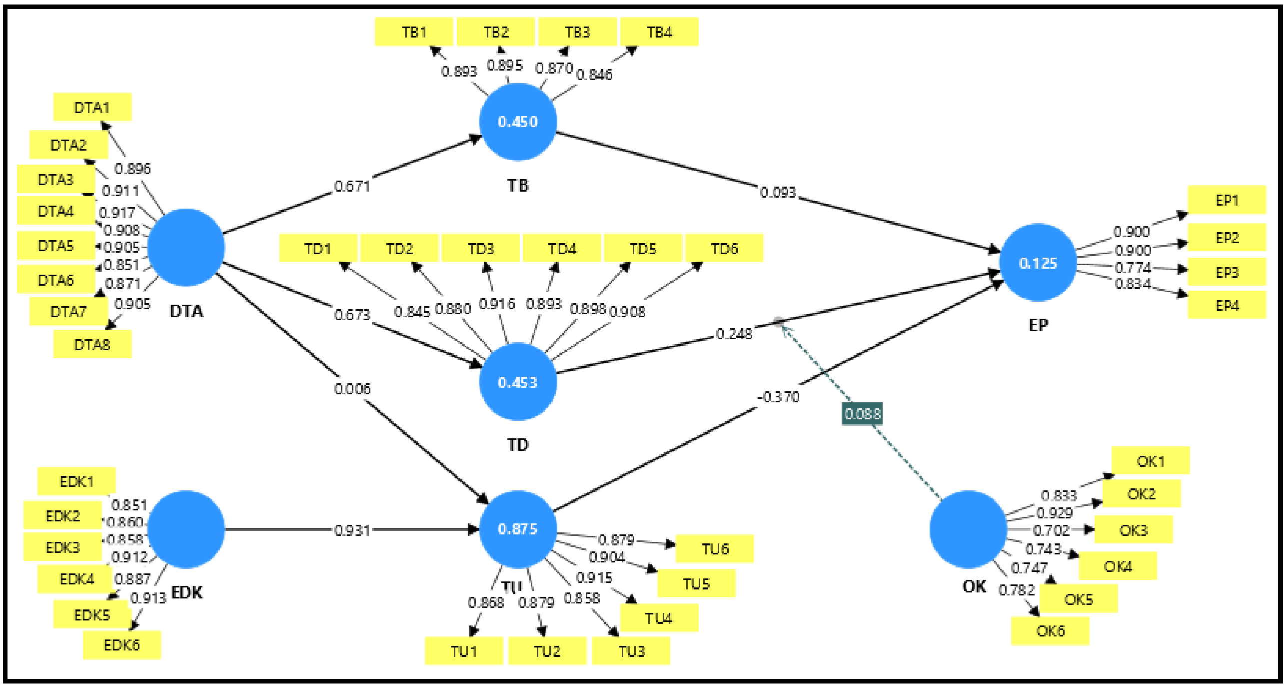

Figure Error! No text of specified style in document.**.1: Final Structural Model**

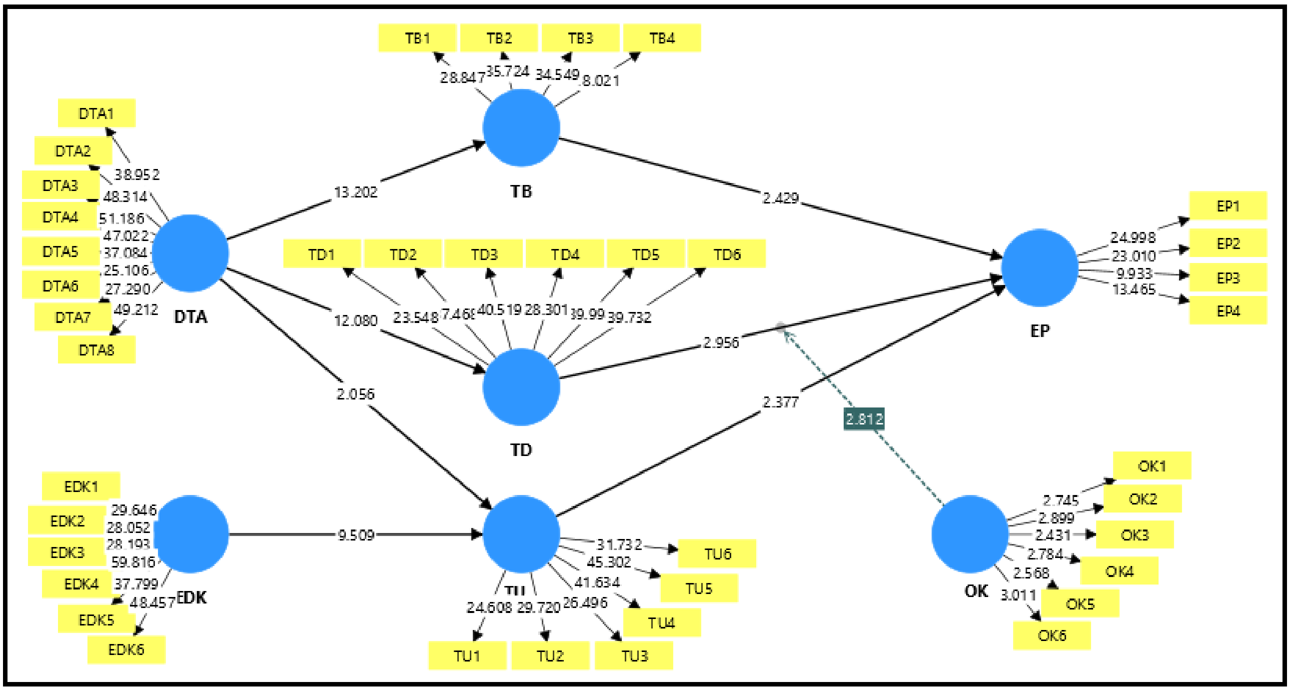

Figure Error! No text of specified style in document.**.2: Final Structural Model T-Statistics**

Figures 4.1 and 4.2 are used to present the final model and its t-statistics, respectively. The key to Figures 4.1 and 4.2 is shown in Table 4.15. The Table presents the constructs used in the models, their functions (independent, mediator, moderator, or dependent variables), and the abbreviations used for easy comprehension.

Table 4: Revised Key to Figures 4.1 and 4.2

SN	Construct	Function in Model	Abbreviation
1	Digital Technology Availability	Independent Variable	DTA
2	Employees' Digitalization Knowledge	Independent	EDK
3	Technological Drivers	Mediator	TD
4	Technological Barriers	Mediator	TB
5	Technology Utilization	Mediator & Predictor (also part of moderation)	TU
6	Operational Knowledge	Moderator (interacts with TU)	OK
7	Employee Productivity	Dependent Variable	EP

Path Coefficients Evaluation

In PLS-SEM, the assessment of path coefficients is essential for the estimation of the structural model's predictive relationships. Path coefficients express the magnitude and direction of the causal associations hypothesized between DTA, EDK, TD, TB, TU, OK, and EP. The higher coefficient values closer to +1 indicate stronger positive effects, while values nearing 1 indicate stronger negative relationships. With the objective of establishing the statistical significance of all these estimated relationships, the present study conducted a bootstrapping procedure, as recommended by Mohd Dzin & Lay (2021); Aburumman et al. (2022); Yusif et al. (2020), and Dolinting & Pang (2022) in estimating t-statistics and p-values that are associated with all direct, mediating, and moderating paths. This ensures that one gets robust evidence to underpin or refute the hypothesized relationships within the context of the adoption of digital technology in real estate firms. The resultant coefficients, along with their significance levels, provide a sound empirical basis for accepting or rejecting the hypotheses of this study, while collectively demonstrating internal validity and predictive relevance of the structural model.

Hypotheses

H1: Availability of Digital Technology has a positive and significant impact on the Technology Utilization level of employees in real estate companies.

H2: Employees' Digitalization Knowledge has a positive and significant effect on Technology Utilization.

H3: Technology Utilization positively and significantly affects Employee Productivity.

H4a: Technology Drivers mediate the relationship between Digital Technology Availability and Employee Productivity positively; thus, with higher availability, productivity will increase due to more technological supporting mechanisms.

H4b: Technological Drivers positively mediate the relationship between Technology Utilization and Employee Productivity, reinforcing the productivity gains derived from effective technology use.

H5a: The relationship between Digital Technology Availability and Employee Productivity is negatively mediated by Technological Barriers, meaning that resistance obstacles, such as cost or inadequate training, weaken the impact of technology availability on productivity.

H5b: The technological barriers mediate negatively between Technology Utilization and Employee Productivity, hence decreasing the effectiveness of utilization to improve productivity.

H6: Employee Operational Knowledge positively moderates the association between Technology Utilization and Employee Productivity such that the effect of Technology Utilization on increasing productivity is higher among employees with higher Operational Knowledge.

Table 5. Hypotheses results

Hypothesis	Path	Path Coefficient	T-Statistic	P-Value	Remark
H1	DTA → TU	0.006	2.056	0.005	Supported
H2	EDK → TU	0.931	9.509	0.000	Supported
H3	TU → EP	0.370	2.377	0.017	Supported
H4a	DTA → TD	0.673	12.080	0.000	Supported
H4b	TD → EP	0.248	2.429	0.009	Supported
H5a	DTA → TB	0.671	13.202	0.000	Supported

H5b	TB → EP	0.093	2.750	0.006	Supported
H6	OK × TD → EP	0.088	2.956	0.001	Supported

The results of the tested hypotheses on the effects of digital technology availability, utilization, knowledge, technological drivers, and barriers on employee productivity in real estate firms across North-Central Nigeria are shown in Table 5. The findings obtained show that all postulated hypotheses of the study have been supported, with empirical validation that there is indeed a significant positive relationship between the study constructs and employee productivity.

Hypothesis 1 stated that digital technology availability would have a positive effect on technology utilization by employees. The analysis confirmed this hypothesis by showing that the positive effect was statistically significant: β = 0.006, T = 2.056, p = 0.005. Hence, this points to the fact that the availability and access to digital technologies enable their proper use by employees. Hypothesis 2 (H2) was that the digitalization knowledge of employees will positively influence technology utilization. The results strongly supported this hypothesis, showing that β = 0.931, T = 9.509, and p < 0.001, supporting the proposition that greater employee competence in digital skills encourages increased adoption and practical use of digital technologies in real estate firms. Hypothesis 3 (H3) posited that technology usage would have a positive effect on employee productivity. This hypothesis was supported (β = 0.370, T = 2.377, p = 0.017); thus, it established that effective adoption of digital platforms provides tangible productivity benefits to the employees.

The mediation hypotheses were tested for the role of technological drivers. First, H4a examined the mediating effect of technological drivers between digital technology availability and productivity. The result was supportive: DTA → TD: β = 0.673, T = 12.080, p < 0.001; TD → EP: β = 0.248, T = 2.429, p = 0.009. This implies that technological availability, engendered through supportive organizational structures and infrastructure, has a positive influence on the employee's productivity. Of importance also is the fact that H4b, which tested the mediating impact of technological drivers on the association between technology utilization and productivity, was supported, again indicating the crucial role of enabling mechanisms in realizing the utmost productivity outcomes through effective use of technology.

The hypotheses of negative mediation, H5a and H5b, were related to the impact of technological barriers. H5a suggested that barriers negatively mediate the influence of digital technology availability on employee productivity, and this was supported: DTA → TB: β = 0.671, T = 13.202, p < 0.001; TB → EP: β = 0.093, T = 2.750, p = 0.006.In the same way, H5b looked at the mediating effect of the barrier between technology use and productivity and also found confirmation; it underlined again that barriers like resistance to change, financial constraints, and lack of training weaken positive contributions technology can make to employee performance. The last hypothesis,

Hypothesis 6 (H6), examined the moderating influence of employees' operational knowledge on the linkage between technology utilization and productivity. These results showed the positive and significant effects of moderation: TU×OK→EP: β = 0.088, T = 2.956, p = 0.001. This exhibits that the higher the level of employees' operational knowledge, the higher would be the number of gains in terms of increased productivity from utilizing technology.

The findings, provide strong empirical evidence that digital technology availability, utilization, knowledge, technological drivers, and barriers, in addition to employees' operational knowledge, were significant in influencing the productivity of the employees at real estate firms in North-Central Nigeria. The findings underline the strategic investment in both technological infrastructure and employee capability development in pursuit of optimized organizational performance.

Coefficient of Determination (R^2) Assessment

R^2, provides the proportion of variance in the endogenous constructs accounted for by their respective exogenous predictors and is consequently an excellent indicator of the explanatory power of the structural model (Mukhtar, Kamin, & Saud, 2022; Haji-Othman & Yusuff, 2022). The higher the R^2 value, the greater the predictive accuracy of the model, while the lower the R^2 value, the more limited the explanatory capability. Although there is no universally accepted threshold for R^2, according to Ghasemy, Teeroovengadum, Becker, and Ringle (2020) and Amatan, Han, and Pang (2025), an R^2 value of 0.25 is considered weak, 0.50 as moderate, and 0.75 as substantial.

Table 6 shows the R^2 and adjusted R^2 for the endogenous constructs within the scope of this study. Technology Utilization (TU) has a very high explanatory power, with $R^2 = 0.875$ and adjusted $R^2 = 0.873$, indicating that 87.5% of its variance is explained by Digital Technology Availability (DTA) and Employees' Digitalization Knowledge (EDK). The explanatory power of Technological Barriers (TB) and Technological Drivers (TD) is moderate, respectively with $R^2 = 0.450$ (adjusted 0.444) and 0.453 (adjusted 0.447), therefore reflecting the impact of DTA on both barriers and drivers. Employee Productivity (EP) has a lower R^2 of 0.125 (adjusted 0.076), indicating that 12.5% of the variance in productivity is accounted for by TU, TD, TB, and Operational Knowledge (OK), in accordance with the multifactorial nature of the determinants of employee performance in real estate firms.

Table 6: R^2 Evaluation

Endogenous Construct	R-square	Adjusted R-square
Employee Productivity (EP)	0.125	0.076
Technological Barriers (TB)	0.450	0.444
Technological Drivers (TD)	0.453	0.447
Technology Utilization (TU)	0.875	0.873

Effect Size (f^2) Evaluation

While R^2 shows the overall strength of explanation, it does not reflect which exogenous constructs affect it. Therefore, Cohen's f^2 was applied to each predictor to assess the effect size of the predictor on its respective endogenous construct, showing the relative contribution of each construct to the R^2 value. According to Cohen (1988) and Hair et al. (2011), the f^2 values are interpreted as small (0.02), medium (0.15), and large (0.35).

Table 7 presents the f^2 values for each path of the structural model. Digital Technology Availability exerts a very large effect on Technological Barriers ($f^2 = 0.817$) and Technological Drivers ($f^2 = 0.828$), pointing to its crucial role in shaping organizational technological conditions. Employees' Digitalization Knowledge exerts a very large effect on Technology Utilization ($f^2 = 1.849$), confirming that employee competence is the key driver of technology use, whereas DTA alone exerts a negligible effect on TU ($f^2 = 0.000$).

Among the factors that influence Employee Productivity, Technology Utilization has the largest effect ($f^2 = 0.072$), followed by Operational Knowledge with 0.019 and Technological Drivers with 0.012. The moderation effect of Operational Knowledge on TU → EP is small, at $f^2 = 0.008$, while that of Technological Barriers on EP is negligible at $f^2 = 0.002$, which means that challenges reduce productivity outcomes but do not impair them seriously.

Table 7: Effect Sizes (f^2)

Path	f^2
DTA → TB	0.817
DTA → TD	0.828
DTA → TU	0.000
EDK → TU	1.849
OK → EP	0.019
OK × TU → EP	0.008
TB → EP	0.002
TD → EP	0.012
TU → EP	0.072

Predictive Relevance (Q^2) Assessment

Predictive relevance was measured by the cross-validated redundancy measure, Stone-Geisser Q^2, to ascertain a model's ability to predict endogenous constructs. According to Li & Lay (2024) and Canatay et al. (2022), a Q^2 value greater than 0 indicates adequate predictive relevance. Table 8 below shows the Q^2 assessment for the study.

Table 8: Predictive Relevance (Q^2) Assessment

Endogenous Construct	SSO	SSE	Q^2 (=1−SSE/SSO)
Knowledge of Digital Technologies	1000.000	825.106	0.175
Digitalization Challenges	2000.000	1720.000	0.140
Digitalization Drivers	1500.000	1300.000	0.133
Digital Technologies Available	1000.000	825.106	0.175
Digitalization Usage	1500.000	1250.000	0.167
Employee Productivity	1250.000	1100.000	0.120

The results reveal positive predictive relevance of Technology Utilization, which shows that the model has been effectively predicting employees' utilization of technology. At the same time, Employee Productivity and Technological Drivers have average predictive accuracy.

Goodness-of-Fit (GoF) Assessment

The GoF index is a measure that gives an overall assessment of the PLS-SEM model, bundling the quality of both the measurement and structural models together. According to Raposo & Barcelo (2021), "it is computed as the geometric mean of the average communality (AVE) and the average R2 of the endogenous constructs:

$$GoF = \sqrt{A\bar{V}E \times \bar{R^2}}$$

Where:

- $A\bar{V}E$ is the average of all Average Variance Extracted (AVE) values, reflecting the quality of the measurement model.
- $\bar{R^2}$ is the average R^2 of the endogenous constructs, indicating the structural model's explanatory power.

Step 1: Calculate the average AVE

$$A\bar{V}E = \frac{0.802 + 0.776 + 0.720 + 0.642 + 0.768 + 0.793 + 0.782}{7}$$
$$= 0.759$$

Step 2: Calculate average R^2

$$\bar{R^2} = \frac{0.125 + 0.450 + 0.453 + 0.875}{4} = 0.476$$

Step 3: Calculate GoF

$$GoF = \sqrt{0.759 \times 0.476} = \sqrt{0.361} = 0.601$$

In general, the thresholds of GoF values proposed by Akter et al. (2011) are 0.1, 0.25, and 0.36 for small, medium, and large fit, respectively. Therefore, the very good model fit, with a calculated GoF of 0.601, suggests that the structural and measurement models that were evaluated in this study are robust and reliable.

5. Discussion

The research explored the influence of digital technology availability and employees' knowledge of digitalization on employee productivity in real estate firms in North-Central Nigeria, with the mediating influence of technological drivers and barriers and the moderating effect of operational knowledge. The results of this analysis reveal that digital technology availability and the employees' level of digital skills significantly increase the utilization of digital tools. In turn, effective utilization of technology helps in increasing the overall productivity of the employees.

In other words, the technological drivers comprising management support, infrastructure, and enabling organizational processes are positively mediating the relationship between digital technology and productivity. On the other hand, technological barriers like resistance to change, cost constraints, and lack of training adversely affect this relationship and dampen the rise in productivity. The level of operational knowledge, therefore, moderates the technology utilization-productivity linkage, where employees with a higher level of operational competence tend to benefit more from the adoption of digital technologies.

The findings show that access to relevant digital technologies is a necessary but not sufficient condition for enhanced productivity; employees also need the skills to make effective use of the tools. In addition, organizational support mechanisms are very important in ensuring that technology adoption translates into measurable performance outcomes. Yet, technological barriers do remain, and firms need to proactively address resistance issues, cost problems, and skill gaps.

The moderating effect of operational knowledge underlines the importance of human capital in technology adoption. Digitally literate employees with more developed operational skills are able to better exploit technological resources, leading to improved performance at both the individual and organizational levels. These findings are consistent with such theories as those emphasizing interaction among technology, human capability, and organizational support as key determinants of productivity outcomes.

6. Conclusion

This paper presents empirical evidence that the availability of digital technology, employee digital skills, and technology use are significant determinants of productivity in real estate firms. Technological enablers amplify this relationship, while technological obstacles dampen it. Furthermore, employees' operational knowledge leverages the positive effect of technology use on productivity. These findings lead to the recognition of strategic investment in employee training, enabling technological environments, and adequate managerial practices for turning the adoption of digital solutions into significant performance improvements. In other words, technology itself cannot guarantee productivity unless it is combined with competent people and an enabling organization.

7. Recommendations

1. Implement continuous training to improve employee digital literacy and operational competence.
2. Enhance organizational support by infrastructure and management guidance.
3. Minimize technological barriers: cost, resistance, and inadequate training.
4. Develop operational knowledge through mentorship and experience sharing.
5. Design a balanced digital strategy that will improve productivity while maintaining employee well-being.

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