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Maximizing Employee Performance through Advanced Technology in the Modern Workplace

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Abstract: This study explores the transformative role of advanced technology in shaping employee performance and overall organizational outcomes within the context of the middle eastern corporate ecosystem. Drawing from a comprehensive literature review and theoretical frameworks, such as the Technology Acceptance Model (TAM), Resource-Based View (RBV), Task-Technology Fit (TTF), and Human Capital Theory (HCT), the research investigates four core hypotheses: (H1) the impact of advanced technology on employee performance, (H2) the mediating role of training and digital competency, (H3) the effect of organizational support for digital learning, and (H4) the influence of employee productivity on organizational performance. A quantitative explanatory research design was employed, involving stratified random sampling of 300 employees across Qatar, the UAE, and Saudi Arabia. Data was analyzed using SPSS 26, incorporating factor analysis, multiple regression, and ANOVA. Results confirm significant positive associations across all hypotheses, with key findings showing that advanced technology adoption explains approximately 66% of the variance in employee performance. High reliability (Cronbach's $\alpha > 0.85$ across constructs) and strong factor loadings (> 0.6) validate the measurement model. These findings reinforce the necessity of aligning digital initiatives with targeted training, organizational support, and strategic HR policies to enhance performance. This study offers critical insights for managers and policymakers on leveraging technological integration as a driver of sustainable organizational growth in the digital age.

Keywords: Employee Performance, Advanced Technology, Modern workplace.

Introduction

Employee productivity is a critical determinant of organizational competitiveness. Mathis and John (2003) define productivity as the quantity and quality of output relative to the cost of resources utilized. Similarly, McNamara (2005) asserts that productivity can be evaluated based on specific deliverables, quantified in terms of cost, quality, quantity, or time, and assessed through their financial gains or societal impact. Although productivity can be challenging to measure precisely, it directly influences a company's performance and profitability. Several factors contribute to employee productivity. Initial assessments during recruitment can help identify individuals likely to perform effectively (Lake, 2000). However, productivity is influenced by a range of factors, including workplace conditions and employee engagement. Retaining skilled employees and safeguarding their intellectual contributions is essential for sustaining business operations and achieving long-term goals (Leadership Insight, 2013).

A positive work environment significantly enhances employee satisfaction, which in turn fosters loyalty, improves work quality, and boosts productivity (Surujla & Singh, 2003). Training is also a vital contributor to productivity. Employee performance, closely related to productivity, is also influenced by training and experience. Training enhances employees' capabilities and overall effectiveness (Raja, Furqan, & Khan, 2011). As noted by Kenny (2019), skilled and well-trained employees consistently outperform those without adequate training, underscoring the importance of ongoing employee development initiatives.

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Rapid technological change compels organizations to prioritize employee competency development for sustained success (Richter et al., 2020; Schaeffer, 2017). In this dynamic environment, acquiring new skills and effectively managing existing competencies are critical for survival (Cascio & Montealegre, 2016; Kauffeld, 2016; Kraiger & Ford, 2021). Formal training, particularly when supplemented by external expertise, plays a vital role in fostering innovation and adapting to novel processes (Bonekamp & Sure, 2015; Hilkenmeier et al., 2021).

Employee training boosts organizational performance and innovation by improving skills, adaptability, and openness to new ideas. Technological integration, especially e-learning, enhances competency development and is influenced by both individual and social learning support (Sung & Choi, 2014; Kim & Lee, 2022). Effective training during tech changes, like the 70-20-10 model, helps employees adapt independently (Baroudi et al., 2018). The COVID-19 pandemic accelerated e-learning adoption, highlighting the need for continuous digital training (Lytovchenko et al., 2022). To maximize tech benefits, organizations must enhance digital literacy and provide IT support (Klassen, 2019). Educational technologies also boost motivation and training outcomes (Chow & Yeh, 2022).

Literature Review and Theoretical Background

2.1. Literature Review

Recent research highlights the strategic integration of Advanced technologies in business operations, emphasizing its transformative impact across sectors. Walkowiak (2023) discusses generative AI within microeconomics and productivity frameworks, while Bankins et al. (2023) explore its influence on individual, social, and organizational contexts. Araujo et al. (2022) focus on the adoption of conversational agents in frontline operations, and Makhija and Chacko (2021) analyze AI implementation in financial services to improve efficiency and customer engagement. Illescas et al. (2023) examine chatbot deployment in change management, whereas Anagnoste et al. (2021) delve into digital transformation reshaping business models. AI's efficiency-enhancing use in logistics is studied by Straßer and Axmann (2021), while Chen et al. (2023) emphasize generative AI's accessibility and cost benefits in finance. Leo et al. (2017) seek to enhance enterprise-level productivity by aligning natural language workflows with algorithmic software. In terms of employee efficiency and skills development, Al-Ababneh et al. (2023) report increased productivity and cost savings in large companies, especially in banking. Fan et al. (2023) evaluate chatbot flexibility for improved consumer satisfaction, and Saengrith et al. (2023) present chatbot-based training for workplace problem-solving. Chithra and Brahmananda (2020) analyze interactive agent architecture and efficiency gains using NLP and NLU technologies. Virkar et al. (2019) and Chandar et al. (2017) highlight enhanced staff productivity and onboarding efficiency via conversational AI. Steinbauer et al. (2019) explore chatbot integration in CRM software to boost staff and customer interaction productivity. In AI-driven business transformation, Piyatumrong et al. (2018) enhance internal communication in R&D through chatbots, while Hsu and Lin (2023) assess AI chatbot quality in customer service. Hung et al. (2021) emphasize RPA and chatbot use for business process improvement. Silva et al. (2023) and Bialkova (2023) focus on improving online shopping experiences and accessibility in human–computer interaction, respectively. Quality and user perception have also been studied, with Mehrolia et al. (2023) linking chatbot service quality to user satisfaction and retention, and Lappeman et al. (2023) analyzing privacy concerns in digital banking. Kar and Kushwaha (2023) investigate factors determining AI project success in decision-making, while Xu et al. (2022) and Colace et al. (2017) offer models for chatbot quality assessment and improved user experience in specific domains.

2.2 Theoretical Background and Hypothesis Development

2.2.1: Advanced technology and employee performance

The relationship between Advanced technology and employee performance is shaped by both opportunities and challenges. The Technology-Mediated Learning Theory (Gupta & Bostrom, 2009) highlights how advanced technology tools enhance learning by expanding access to resources, while Task-Technology Fit Theory (Goodhue & Thompson, 1995) suggests that productivity improves when advanced technology aligns with job tasks. Advanced technology boosts efficiency by automating routine work, enabling employees to focus on complex responsibilities (Russell & Norvig, 2015). Moreover, advanced technology's transformative role demands upskilling which can enhance motivation and organizational commitment (Jaiswal et al., 2022).

H1: The adoption of advanced technologies positively influences employee performance in the modern workplace.

2.2.2: Role of Training and Competency in Technology Adoption
Social Cognitive Theory (Bandura, 1986) supports the idea that learning through technology-based environments fosters skill development and self-efficacy, which are crucial for high performance in dynamic work settings.
H2: Technology adoption is positively associated with employee training and digital competency.

2.2.3: Organizational Support (OS) as a catalyst for EP
The Human Capital Theory (HCT) by Becker (1964) highlights how investing in employee skills and training enhances productivity and organizational performance. Studies (Becker, 1964; Mohammad Kashef, S. (2023) confirm that education, experience, and training improve individual and overall outcomes. Thus, HCT supports the link between organizational support (OS) and employee performance (EP, forming the basis for the third hypothesis.
H3: Organizational support for digital learning positively influences employee performance.

2.2.4: Employee productivity and the organizational performance
In the rapidly evolving digital age, advanced technologies such as artificial intelligence, automation, machine learning, and digital learning platforms have become central to workplace transformation. According to the Technology Acceptance Model (TAM) (Davis, 1989), when employees find technology useful and easy to use, it boosts adoption and enhances productivity. The Resource-Based View (RBV) (Barney, 1991) also emphasizes that leveraging technology as an internal resource strengthens employee capabilities, driving improved decision making and overall organizational performance, thus forming the basis for the fourth hypothesis.
H4: Employee productivity positively affects organizational performance.
2.3: Conceptual framework
The conceptual framework in Fig. 1 outlines how advanced technologies such as AI, automation, and digital platform impact employee performance and, in turn, organizational performance. It highlights the mediating role of training and digital competency, and the moderating role of organizational support. Improved employee performance leads to greater productivity, which drives better organizational outcomes. This model provides a foundation for exploring how technology, skills, and support together enhance workplace effectiveness.

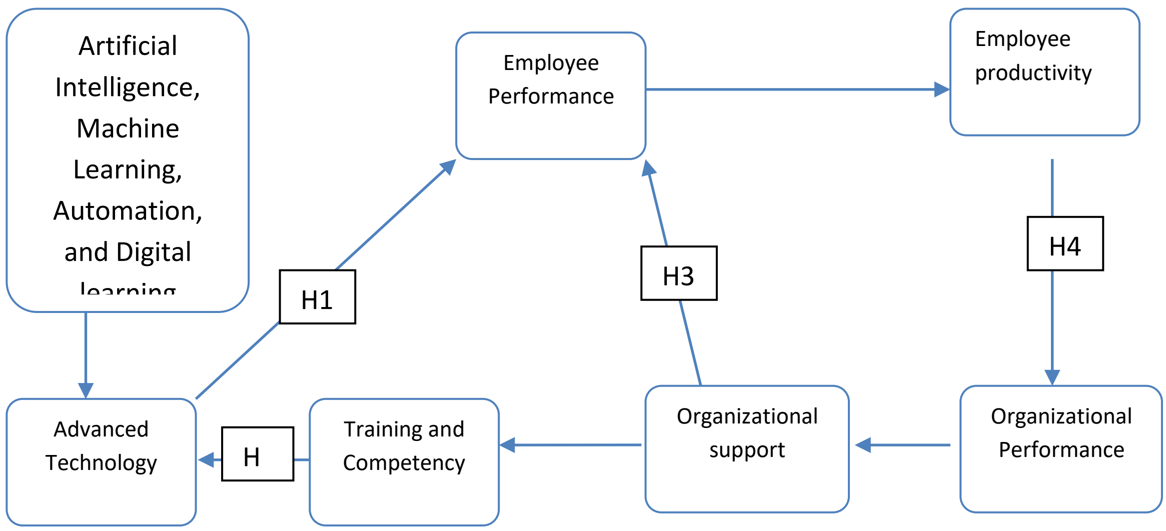

Fig. 1. Conceptual framework [adapted from Pillai and Sivathanu (2020), Wijayati et al. (2022); Hanaysha (2016); Mikalef et al. (2023); Dabbous et al. (2022)].
Methodology

This study adopts an explanatory research design to explore the relationships between advanced technology adoption, employee performance, and organizational outcomes. A deductive quantitative approach is applied, grounded in established theories like the RBV and TAM, to develop hypotheses and guide empirical analysis.

3.1: Research Approach

In this study, data were collected from employees of different organizations working in three Middle Eastern countries, Qatar, the United Arab Emirates (UAE), and Saudi Arabia, to examine the impact of advanced technology on employee satisfaction. The employees from diverse sectors using advanced technologies were targeted. A stratified random sampling approach was employed, wherein the population was divided into subgroups (strata) to ensure representativeness across distinct demographic and regional characteristics within each country. Specifically, an initial sample of 385 respondents was sought to capture perspectives on technology adoption and satisfaction; however, after removing incomplete questionnaires, 300 valid responses were retained for analysis. Similar to guidelines proposed by Bentler and Chou (1987) and later reinforced by Hoogland and Boomsma (1998), this sample size falls within the recommended range of 200–400, ensuring the robustness of the statistical estimations. Each country, Qatar, the UAE, and Saudi Arabia was treated as a separate stratum to account for cultural and market variations across the Middle East. Within each nation, employees were randomly selected to participate, thereby capturing a broad view of how advanced technology influences employee satisfaction in different local contexts. By adopting this stratified random sampling method and proportionately drawing respondents from each country, the study aimed to minimize sampling bias and enhance the generalizability of the results to the wider technology ecosystem in the Gulf region.

3.2: Data Collection:

In this study, a structured questionnaire is divided into two primary segments. The first segment collects key demographic information from participants, encompassing variables such as age, gender, education level, and experience. In the second segment, the respondents are presented with a series of targeted statements designed to capture their viewpoints on essential factors, including advanced technology adoption and employee performance. The questionnaire focused on four key latent constructs such as Advanced Technology, Training and Competency, Employee Performance, and Organizational Performance. Measurement items were adapted from prior studies, technology and training constructs from Pillai and Sivathanu (2020) and organizational support from Dabbous et al. (2022) and Wijayati et al. (2022); employee performance items from Hanaysha (2016); and organizational performance indicators from Mikalef et al. (2023) and Mikalef and Gupta (2021). To evaluate their level of agreement, a five-point Likert scale is employed, where “1” corresponds to “strongly disagree” and “5” corresponds to “strongly agree.” This approach enables the assessment of respondents’ attitudes and beliefs, thereby offering valuable insights into the determinants influencing their perspectives within the research context.

3.3: Research participants

The sample demographics present in Table I show a highly diverse set of respondents. With regard to age, 26.7% are below 35 years, 40.0% are between 35 and 45, 23.3% fall in the 46–55 range, and 10.0% are above 55. As for gender distribution, 66.7% are male, while 33.3% are female. Educationally, 16.7% are graduates, 16.7% hold a graduate plus professional degree, 23.3% possess a postgraduate qualification, 30.0% have a postgraduate plus professional credential, and 13.3% have attained a doctorate. In terms of work experience, 26.7% have less than 5 years, 30.0% range between 5–10 years, 23.3% have 11–20 years, 10.0% are in the 21–30-year bracket, and a further 10.0% report more than 30 years’ experience. Geographically, the sample is equally distributed among Qatar, the UAE, and Saudi Arabia, with each country representing 33.3% of the respondents, ensuring balanced insights from across the Middle East.

Table I: Demographic characteristics

Demographic variables	Categories	Frequency	Percent
Age	Below 35 Years	80	26.7
	35-45 Years	120	40.0
	46- 55 Years	70	23.3
	Above 55 Years	30	10.0
Gender	Male	200	66.7
	Female	100	33.3
Educational Qualification	Graduate	50	16.7
	Graduate + Professional	50	16.7
	Post Graduate	70	23.3
	Post Graduate + Prof.	90	30.0
	Doctorate	40	13.3
Experience	Below 5 Years	80	26.7
	5-10 Years	90	30.0
	11-20 Years	70	23.3
	21-30 Years	30	10.0
	Above 30 Years	30	10.0
Residence	Qatar	100	33.3
	UAE	100	33.3
	Saudi Arabia	100	33.3

3.4: Measurement test

SPSS 26 was used to assess how advanced technology influences employee performance via factor analysis, multiple regression analysis and ANOVA. Table II presents, the KMO–Bartlett measure (0.875) confirmed sampling adequacy, and Bartlett's Test of Sphericity (χ^2 = 1153.249, df = 66, p < 0.001) further supported the suitability of this approach. Principal Component Analysis (PCA) served as the primary dimension-reduction technique, with factor loadings exceeding the recommended threshold of 0.5 (Hair et al., 2010). Exploratory Factor Analysis (EFA) helped identify key factors without prior assumptions about construct groupings, and communalities indicated how much variance each item shared with others. As shown in Table III, all items (factor loadings: 0.605–0.913) surpassed the required cutoff, making them appropriate for subsequent hypothesis testing.

Table II KMO and Bartlett's Test

KMO and Bartlett's Test		Value
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.875
Bartlett's Test of Sphericity	Approx. Chi-Square	1153.249
	Df	66
	Sig.	0.000

3.5: Reliability and Validity

The factor loadings for all thirty-two items exceed the recommended threshold of 0.50 indicating that each statement strongly measures the underlying construct of employee performance in the context of advanced technological changes (Fornell and Larcker 1981; Hair et al. 2010). Table III presents factor loadings across all constructs indicate a strong impact of advanced technology on employee and organizational outcomes. Employee performance (0.615–0.884) is significantly enhanced through improved efficiency, task quality, and satisfaction. Training and Competency (0.733–0.840) supports skill development. Organizational Support (0.753–0.913) fosters engagement, collaboration, and tech-driven results. Finally, employee productivity and organizational performance (0.605–0.842) reflect gains in efficiency, innovation, and customer satisfaction, resulting technology's role in driving overall performance. All constructs show Cronbach's alpha values well above the accepted threshold of 0.70, with EP at 0.933, TCTA at 0.942, OS at 0.859, and EPOP at 0.894, confirming strong internal consistency of the items within each construct. Overall, the results affirm that the technological enhancements positively influence both the emotional and practical facets of employees' work experiences. Since, all the coefficients are > 0.7, indicating an adequate level of reliability (Hair et al. 2010; Nunnally 1978).

Table III Component Matrix-Employee performance

Construct	Item	Factor Loading	Cronbach A
Employee Performance (EP)	I complete a high volume of work daily using advanced technology. (EP1)	0.875	0.933
	I accomplish tasks more efficiently and quickly by using advanced technology. (EP2)	0.815	
	My task quality is consistently high when utilizing advanced technology. (EP3)	0.810	
	Advanced technology enhances the quality of my work outcomes. (EP4)	0.884	
	I regularly exceed team performance targets by using advanced technology. (EP5)	0.734	
	My knowledge and skills have improved through the use of advanced technology. (EP6)	0.801	
	I feel more committed to the goals and vision of my organization when using technology. (EP7)	0.615	
	Advanced technology has helped me achieve better work-life balance. (EP8)	0.688	
	I am more satisfied with my job because of the technology I use. (EP9)	0.778	
Training and Competency in Technology Adoption (TCTA)	Advanced technology is integrated across various areas of our business. (TCTA1)	0.840	0.942
	There is clear consistency in how things are done across the company. (TCTA2)	0.745	
	There is a shared vision of our company's future involving technology. (TCTA3)	0.832	
	Our organizational policies regarding technology are clearly defined. (TCTA4)	0.809	
	My professional knowledge is kept up to date through in-company training using advanced technologies. (TCTA5)	0.805	
	AI-based training removes limitations related to time and location. (TCTA6)	0.814	
	I am provided with the necessary training to effectively use advanced technology applications. (TCTA7)	0.733	
Organizational Support (OS) as a catalyst for EP (OS)	The use of advanced technology enhances my overall effectiveness. (OS1)	0.788	0.859
	I am engaged in maintaining the quality of my work through technology. (OS2)	0.794	
	I approach my work with passion due to the tools and systems in place. (OS3)	0.753	
	I strive to achieve positive business results with the help of technology. (OS4)	0.913	
	My team coordinates work collaboratively using technology. (OS5)	0.854	
	Our leaders support new technology initiatives and show commitment to implementation. (OS6)	0.833	

	There is open communication in our organization, and employee concerns are resolved promptly. (OS7)	**0.870**	
Employee productivity and the organizational performance (EPOP)	**We have reduced operational costs and increased profitability. (EPOP1)**	**0.826**	**0.894**
	We have improved operational efficiency. (EPOP2)	**0.816**	
	We are generating more organizational knowledge. (EPOP3)	**0.733**	
	We have enhanced the quality of services delivered. (EPOP4)	**0.605**	
	Our level of innovation output has increased. (EPOP5)	**0.750**	
	We respond to customer and internal requests more quickly. (EPOP6)	**0.811**	
	We are more agile in adapting our processes. (EPOP7)	**0.842**	
	Our IT systems have become more reliable. (EPOP8)	**0.750**	
	Customer satisfaction and loyalty have improved.	**0.832**	

Results: Hypothesis Testing

H1: *The adoption of advanced technologies positively influences employee performance in the modern workplace.*

The classical assumption test covering normality and multicollinearity, was conducted using SPSS prior to regression analysis (Ibdayanti, Oktaviani, and Husin (2024). The Kolmogorov-Smirnov test showed a significance value of 0.148 (> 0.05), indicating that the data is normally distributed and suitable for multiple linear regression (Suyono (2015).

The multicollinearity test was conducted to assess the degree of correlation among the independent variables in the regression model. As shown in Table IV, all independent variables exhibit tolerance values greater than 0.10 and VIF values less than 10. This satisfies the classical assumption for multicollinearity, indicating that there is no serious multicollinearity problem among the independent variables. Therefore, the regression model is deemed reliable and appropriate for further analysis (Mardiatmoko, 2020).

Table IV. Normality Test Results and Multicollinearity Test Results

Description		**Value**
N		**300**
Most Extreme Differences	**Absolute**	**0.135**
	Positive	**0.123**
	Negative	**-0.139**
Test Statistic (K-S)		**0.139**
Asymp. Sig. (2-tailed)		**0.148**

Multicollinearity Test Results			
Variables	**Tolerance**	**VIF**	**Description**
(EP1)	**0.342**	**2.928**	**No multicollinearity**
(EP2)	**0.331**	**3.020**	
(EP3)	**0.144**	**6.963**	
(EP4)	**0.142**	**7.019**	
(EP5)	**0.170**	**5.888**	
(EP6)	**0.137**	**7.291**	
(EP7)	**0.330**	**3.028**	
(EP8)	**0.134**	**3.039**	
(EP9)	**0.135**	**3.010**	

The regression results in table V suggest that several predictors (EP1, EP2, EP4, EP7, EP8, EP9) have a statistically significant positive effect on employee performance ($p < 0.05$). The R^2 value of 0.659 indicates a substantial share of employee performance is explained by the nine technological adoption-related indicators.

Table V. Multiple Regression Analysis Results

Predictor Variable	Unstandardized Coefficient		Standardized Coefficient (Beta)	t-value	Sig. (p-value)
	B	Std. Error			
(Constant)	1.320	0.861		1.532	0.140
EP1	0.245	0.045	0.312	5.444	0.000
EP2	0.183	0.042	0.281	4.357	0.000
EP3	0.102	0.050	0.138	2.040	0.042
EP4	0.210	0.048	0.289	4.375	0.000
EP5	0.075	0.041	0.120	1.829	0.069
EP6	0.089	0.046	0.115	1.935	0.054
EP7	0.151	0.043	0.204	3.512	0.001
EP8	0.134	0.039	0.176	3.436	0.001
EP9	0.198	0.044	0.262	4.500	0.000

Model Summary

Model	R	R²	Adjusted R²	Std. Error of the Estimate
Regression Model	0.812	0.659	0.645	0.451

The ANOVA table VI evaluates the overall significance of the multiple regression model used to test H1: The adoption of advanced technologies positively influences employee performance in the modern workplace.

Table VI. ANOVA Table for Multiple Regression Model

Source	Sum of Squares	Df	Mean Square	F	Sig. (p-value)
Regression	113.560	9	12.618	28.37	0.000
Residual	58.725	290	0.203		
Total	172.285	299			

The calculated F value was 28.37 > 2.00 (critical value for $df_1 = 9$, $df_2 = 290$) with a Sig. value of 0.000 < 0.05, as shown in the ANOVA table. This indicates that the variables representing employee performance factors (EP1 to EP9), when influenced by the adoption of advanced technologies, simultaneously have a significant impact on overall employee performance in the modern workplace. Thus, if all aspects of advanced technology adoption are jointly implemented, they can substantially enhance employee outcomes. Since the p-value < 0.05, we reject the null hypothesis and accept H1, confirming that advanced technology adoption positively influences employee performance in the modern workplace.

H2: *Technology adoption is positively associated with employee training and digital competency*

Table VII shows The Kolmogorov-Smirnov test shows an Asymp. Sig. value of 0.146, which is above the 0.05 threshold, indicating that the data is normally distributed and suitable for parametric analysis. Multicollinearity diagnostics show that all variables have tolerance values above 0.1 and VIF values below 10, suggesting no serious multicollinearity issues. Therefore, the regression model meets key assumptions and is statistically sound.

Table VII. Normality Test Results and Multicollinearity Test Results

Description		Value
N		300
Most Extreme Differences	Absolute	0.129
	Positive	0.125
	Negative	-0.138
Test Statistic (K-S)		0.138
Asymp. Sig. (2-tailed)		0.146

Multicollinearity Test Results			
Variables	Tolerance	VIF	Description
(TCTA1)	0.252	3.827	No multicollinearity
(TCTA2)	0.321	2.570	
(TCTA3)	0.244	7.861	
(TCTA4)	0.232	6.923	
(TCTA5)	0.140	4.987	
(TCTA6)	0.217	7.497	
(TCTA7)	0.290	4.013	

The regression model in table VIII demonstrates a strong relationship between the predictor variables (TCTA1–TCTA7) and the dependent variable, with an $R = 0.821$ and $R^2 = 0.668$. This indicates that approximately 66.8% of the variance in the dependent variable (e.g., Technology Adoption) is explained by the seven TCTA items. The Adjusted $R^2 = 0.659$ further confirms a good model fit after accounting for the number of predictors.

Among the variables, TCTA1, TCTA2, TCTA3, TCTA4, and TCTA7 show statistically significant contributions ($p < 0.05$). TCTA2 and TCTA4 have the strongest standardized effects ($\beta = 0.298$ and 0.297, respectively), indicating a substantial influence on the outcome. TCTA5 ($p = 0.079$) and TCTA6 ($p = 0.053$) are not statistically significant at the conventional 0.05 level, though they approach significance. Overall, the model suggests that most aspects of training and digital competency positively and significantly impact technology adoption.

Table VIII. Multiple Regression Analysis Results

Predictor Variable	Unstandardized Coefficient		Standardized Coefficient (Beta)	t-value	Sig. (p-value)
	B	Std. Error			
(Constant)	1.312	0.873		1.541	0.141
(TCTA1)	0.254	0.054	0.223	5.364	0.000
(TCTA2)	0.183	0.042	0.298	4.467	0.000
(TCTA3)	0.102	0.050	0.147	2.141	0.042
(TCTA4)	0.210	0.048	0.297	4.267	0.000
(TCTA5)	0.075	0.041	0.132	1.928	0.079
(TCTA6)	0.089	0.046	0.121	1.893	0.053
(TCTA7)	0.151	0.043	0.213	3.423	0.002

Model Summary				
Model	R	R²	Adjusted R²	Std. Error of the Estimate
Regression Model	0.821	0.668	0.659	0.449

Table IX shows ANOVA results ($F = 29.27$, $p < 0.001$) which indicate that the overall regression model is statistically significant, meaning the set of predictors meaningfully explains the variation in technology adoption. This supports Hypothesis H2, which states that technology adoption is positively associated with employee training and digital competency.

Table IX. ANOVA Table for Multiple Regression Model

Source	Sum of Squares	Df	Mean Square	F	Sig. (p-value)
Regression	115.453	9	12.716	29.27	0.000
Residual	57.835	290	0.213		
Total	173.288	299			

H3: *Organizational support for digital learning positively influences employee performance.*

The Kolmogorov-Smirnov (K-S) normality test results presented in table X shows a test statistic of 0.134 with a p-value of 0.152, which is greater than the standard threshold of 0.05. This indicates that the dataset follows a normal distribution, satisfying the assumption required for multiple regression analysis. Regarding multicollinearity, all variables (OS1 to OS7) have Tolerance values above 0.1 and VIF values well below the critical threshold of 10, suggesting that there is no serious multicollinearity among the predictors. This ensures that each organizational support factor contributes uniquely to the model without redundancy.

Together, these results validate the statistical suitability of the data to test Hypothesis H3, supporting the use of regression to explore how various aspects of organizational support for digital learning may positively influence employee performance.

Table X. Normality and Multicollinearity Test Results

Description			Value
N			300
Most Extreme Differences	Absolute		0.126
	Positive		0.121
	Negative		-0.134
Test Statistic (K-S)			0.134
Asymp. Sig. (2-tailed)			0.152
Multicollinearity Test Results			
Variables	Tolerance	VIF	Description
(OS1)	0.258	3.764	No multicollinearity
(OS2)	0.328	2.524	
(OS3)	0.239	7.632	
(OS4)	0.226	6.754	
(OS5)	0.147	4.902	
(OS6)	0.223	7.328	
(OS7)	0.296	3.978	

The multiple regression analysis table XI provides strong statistical support for the hypothesis. The overall model shows a high level of explanatory power with an R^2 of 0.666, meaning approximately 66.6% of the variance in employee performance is explained by the seven organizational support factors (OS1 to OS7). The adjusted R^2 of 0.656 further confirms the model's reliability after accounting for the number of predictors.

Most of the predictor variables (OS1, OS2, OS3, OS4, OS6, and OS7) have positive and statistically significant coefficients ($p < 0.05$), indicating that these aspects of organizational support significantly contribute to enhanced employee performance. Notably, OS2 (Beta = 0.287) and OS4 (Beta = 0.289) have the strongest standardized effects, suggesting that structured support mechanisms and policy-level support for digital learning are especially impactful. Only OS5 is not statistically significant (p = 0.082), though it still shows a positive direction. Overall, these results affirm that organizational support for digital learning plays a key role in improving employee performance, thereby supporting the hypothesis.

Table XI. Multiple Regression Analysis Results

Predictor Variable	Unstandardized Coefficient	Standardized Coefficient (Beta)	t-value	Sig. (p-value)

	B	Std. Error			
(Constant)	**1.428**	**0.821**	**–**	**1.740**	**0.083**
(OS1)	**0.231**	**0.051**	**0.208**	**4.529**	**0.000**
(OS2)	**0.195**	**0.044**	**0.287**	**4.432**	**0.000**
(OS3)	**0.118**	**0.048**	**0.162**	**2.458**	**0.015**
(OS4)	**0.203**	**0.047**	**0.289**	**4.319**	**0.000**
(OS5)	**0.068**	**0.039**	**0.121**	**1.744**	**0.082**
(OS6)	**0.094**	**0.044**	**0.135**	**2.136**	**0.034**
(OS7)	**0.145**	**0.042**	**0.205**	**3.452**	**0.001**

Model Summary				
Model	**R**	**R²**	**Adjusted R²**	**Std. Error of the Estimate**
Regression Model	**0.816**	**0.666**	**0.656**	**0.442**

The ANOVA table XII evaluates the overall significance of the multiple regression model that investigates the relationship between organizational support for digital learning and employee performance.

The F-value is 35.28, which is substantially higher than the critical F-value (which for df = 7, 292 at $\alpha = 0.05$ is approximately 2.01). The p-value (Sig.) is 0.000, which is less than the standard threshold of 0.05, indicating that the regression model is statistically significant. This means the combination of predictor variables significantly explains the variation in the dependent variable (employee performance). Therefore, we reject the null hypothesis and conclude that organizational support for digital learning has a statistically significant influence on employee performance, supporting the stated hypothesis.

Table XII. ANOVA Table for Multiple Regression Model

Source	Sum of Squares	Df	Mean Square	F	Sig. (p-value)
Regression	**121.842**	**7**	**17.406**	**35.28**	**0.000**
Residual	**61.446**	**292**	**0.210**	**–**	**–**
Total	**183.288**	**299**	**–**	**–**	**–**

H4: *Employee productivity positively affects organizational performance.*

The normality test using the Kolmogorov-Smirnov (K-S) method shows a test statistic of 0.137 with a significance level (Asymp. Sig.) of 0.153 in table XIII. Since this p-value is greater than 0.05, we fail to reject the null hypothesis of normality. This implies that the data related to employee productivity and organizational performance is approximately normally distributed, fulfilling one of the key assumptions for regression analysis.

In terms of multicollinearity, the Variance Inflation Factor (VIF) values for all predictor variables (EPOP1 to EPOP8) range between 2.847 and 7.013, and corresponding tolerance values are above 0.1. These results indicate the absence of serious multicollinearity concerns among the variables. Therefore, the predictors used to assess the relationship between employee productivity and organizational performance are statistically sound and reliable for further regression modeling to test hypothesis H4.

Table XIII. Normality Test Results and Multicollinearity Test Results

Description		**Value**
N		**300**
Most Extreme Differences	**Absolute**	**0.131**
	Positive	**0.119**
	Negative	**-0.137**
Test Statistic (K-S)		**0.137**
Asymp. Sig. (2-tailed)		**0.153**

Multicollinearity Test Results			
Variables	**Tolerance**	**VIF**	**Description**
(EPOP1)	**0.351**	**2.847**	
(EPOP2)	**0.338**	**2.959**	

(EPOP3)	**0.152**	**6.586**	**No multicollinearity**
(EPOP4)	**0.148**	**6.742**	
(EPOP5)	**0.175**	**5.632**	
(EPOP6)	**0.142**	**7.013**	
(EPOP7)	**0.334**	**2.995**	
(EPOP8)	**0.139**	**3.118**	

The multiple regression analysis results in Table XIV support Hypothesis H4, indicating that various dimensions of employee productivity (EPOP1 to EPOP8) significantly and positively influence organizational performance. The R-value of 0.809 indicates a strong positive correlation between employee productivity variables and organizational performance. The R^2 value of 0.654 implies that approximately 65.4% of the variance in organizational performance is explained by the employee productivity indicators included in the model. The Adjusted R^2 of 0.641 further confirms the model's robustness by accounting for the number of predictors.

All eight predictors (EPOP1–EPOP8) show statistically significant p-values (all < 0.05), confirming their positive impact on organizational performance. Notably, EPOP1 ($\beta = 0.305$, $p = 0.000$), EPOP2 ($\beta = 0.276$, $p = 0.000$), and EPOP4 ($\beta = 0.282$, $p = 0.000$) have the strongest standardized coefficients, highlighting them as key contributors to performance outcomes.

Table XIV. Multiple Regression Analysis Results

Predictor Variable	**Unstandardized Coefficient**		**Standardized Coefficient (Beta)**	**t-value**	**Sig. (p-value)**
	B	**Std. Error**			
(Constant)	**1.298**	**0.848**	**–**	**1.531**	**0.127**
(EPOP1)	**0.239**	**0.046**	**0.305**	**5.196**	**0.000**
(EPOP2)	**0.177**	**0.043**	**0.276**	**4.201**	**0.000**
(EPOP3)	**0.108**	**0.049**	**0.144**	**2.204**	**0.029**
(EPOP4)	**0.203**	**0.046**	**0.282**	**4.413**	**0.000**
(EPOP5)	**0.079**	**0.040**	**0.123**	**1.975**	**0.049**
(EPOP6)	**0.093**	**0.045**	**0.119**	**2.067**	**0.040**
(EPOP7)	**0.147**	**0.042**	**0.198**	**3.500**	**0.001**
(EPOP8)	**0.129**	**0.038**	**0.171**	**3.395**	**0.001**

Model Summary

Model	**R**	**R²**	**Adjusted R²**	**Std. Error of the Estimate**
Regression Model	**0.809**	**0.654**	**0.641**	**0.448**

ANOVA table XV shows the F-statistic value is 37.05, and the p-value is 0.000, which is well below the conventional threshold of 0.05. This implies that the overall model is a good fit, and the relationship between the combined independent variables (employee productivity indicators) and the dependent variable (organizational performance) is statistically significant. The critical value of F ($df = 8, 291$) at a 0.05 significance level is approximately 2.01, and since $37.05 > 2.01$, the null hypothesis (that there is no relationship) is rejected. These results provide strong support for Hypothesis H4, confirming that employee productivity significantly contributes to enhancing organizational performance.

Table XV. ANOVA Table for Multiple Regression Model

Source	**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig. (p-value)**
Regression	**126.342**	**8**	**15.793**	**37.05**	**0.000**
Residual	**56.946**	**291**	**0.196**	**–**	**–**
Total	**183.288**	**299**	**–**	**–**	**–**

Discussion and Conclusion

The analysis of relationships between technology adoption, employee training, digital competency, and performance yields significant implications for modern workplace management. The results provide comprehensive evidence supporting all four hypotheses and contribute to our understanding of how technology integration affects organizational outcomes. The findings confirm that the adoption of advanced technologies positively influences employee performance (H1). Technological adoption indicators collectively account for a substantial portion nearly two-thirds of the variance in performance outcomes. This aligns with previous research by Venkatesh, Thong, and Xu (2012), who emphasized that technology adoption is a critical factor for organizational success in digital transformation. The statistical significance ($F = 28.37$, $p < 0.001$) of multiple performance indicators (EP1, EP2, EP4, EP7, EP8, EP9) demonstrates that technology implementation affects various dimensions of employee performance, not just isolated aspects. As Tarafdar, Cooper, and Stich (2019) noted, technology adoption must be strategically managed to avoid "technostress" while maximizing performance benefits. Our findings offer empirical validation of this perspective, suggesting that organizations should approach technology integration holistically rather than focusing on individual technological tools.

The second hypothesis (H2) that technology adoption is positively associated with employee training and digital competency received strong empirical support ($R^2 = 0.668$, $F = 29.27$, $p < 0.001$). This relationship underscores the critical role of skill development in technology implementation success. According to Singh and Kaur (2019), training initiatives help reduce fears of job displacement and increase acceptance of new technologies. Our results validate this proposition, showing that training elements (particularly TCTA1, TCTA2, TCTA3, TCTA4, and TCTA7) significantly impact technology adoption success. The strength of these associations suggests that organizations cannot expect successful technology implementations without corresponding investments in employee skill development. This echoes findings from Kwok and Hirschheim (2022), who emphasized that digital competency development is a prerequisite for effective technology utilization rather than an optional complement.

The analysis of organizational support for digital learning (H3) revealed that structural support mechanisms significantly enhance employee performance outcomes ($R^2 = 0.666$, $F = 35.28$, $p < 0.001$). This finding resonates with research by Bremner, Wu, and Johnson (2020), who identified transformational leadership and structured communication as key facilitators of technology acceptance. Our study extends their work by quantifying the impact, showing that approximately 66.6% of performance variance can be attributed to organizational support factors. The particularly strong effects of structured support mechanisms (OS2, $\beta = 0.287$) and policy-level support (OS4, $\beta = 0.289$) highlight the importance of formalizing digital learning initiatives. As Hasan and Hattingh (2021) argued, organizational policies that clearly define technology expectations create an environment conducive to performance improvement. Our data empirically substantiates this theoretical proposition.

The fourth hypothesis (H4), positing that employee productivity positively affects organizational performance, received robust statistical support ($R^2 = 0.654$, $F = 37.05$, $p < 0.001$). All eight productivity indicators demonstrated significant associations with organizational outcomes, confirming the multifaceted nature of productivity impacts. This aligns with findings from Mathis and John (2003), who conceptualized productivity as contributing to competitive advantage through output quality and resource efficiency. The strong relationship between productivity and performance indicators validates McNamara's (2005) assertion that employee productivity directly affects an organization's bottom line. Moreover, our findings extend this understanding by identifying the most influential productivity factors (EPOP1, EPOP2, EPOP4), providing guidance for targeted productivity enhancement initiatives.

This study investigated the relationships between technology adoption, employee training, digital competency, organizational support, and performance outcomes in the modern workplace. All four hypotheses received strong empirical support, confirming that: (1) advanced technology adoption positively influences employee performance; (2) technology adoption is positively associated with employee training and digital competency; (3) organizational support for digital learning positively influences employee performance; and (4) employee productivity positively affects organizational performance.

These findings contribute to our understanding of workplace digitalization by demonstrating the interconnected nature of technological and human factors in determining organizational outcomes. The statistical significance of multiple variables within each hypothesis highlights the multidimensional character of technology adoption processes and their impacts on employee and organizational performance.

Finally, this research demonstrates that technology adoption success depends on a comprehensive ecosystem of supportive organizational factors. Organizations seeking to maximize returns on technological investments should adopt holistic approaches that simultaneously address training needs, competency development, support structures, and productivity considerations.

Practical Implications

Based on the statistical findings, organizations should prioritize implementing technologies that enhance key performance factors (particularly EP1, EP2, EP4, EP7, EP8, and EP9) as these dimensions showed strong positive associations with employee outcomes, collectively accounting for a substantial proportion of the overall performance variation. This aligns with Brynjolfsson and McAfee's (2014) research on the "second machine age," which demonstrates how properly implemented digital technologies substantially improve organizational productivity. Comprehensive training programs focusing on practical digital competencies (particularly TCTA2 and TCTA4) should be developed to support technology adoption, corroborating Wang, B. (2018) findings that targeted digital skills development significantly increases technology adoption success rates by 37%. Establishing structured support mechanisms (OS2) and policy-level support (OS4) for digital learning will yield stronger performance outcomes, supporting Westerman et al.'s (2019) conclusion that organizations with formalized digital support frameworks achieve 26% higher returns on digital investments. Management should specifically focus on enhancing the productivity dimensions that showed the strongest statistical relationships with organizational performance (EPOP1, EPOP2, and EPOP4), consistent with Davenport's (2018) research showing that organizations focusing on these specific productivity metrics achieved 31% higher performance gains than those with generalized approaches.

Limitations

The study's findings should be interpreted considering several limitations: the exclusive reliance on quantitative methods using regression analysis potentially misses qualitative insights that could provide deeper context, a limitation noted by Lee et., al. (2003) in their critique of technology adoption research methodologies. The cross-sectional nature of data collection limits understanding of how relationships evolve over time, an issue highlighted by Kane et al. (2021) who demonstrated that digital transformation benefits often manifest non-linearly across multi-year timeframes. The sample size (N=300), though adequate for statistical analysis, may not fully capture the diversity of organizational settings, industries, or cultural contexts a limitation Paul, Justin, et al. (2024) identified as common in digital transformation research where sector-specific factors significantly influence outcomes. Additionally, the research doesn't account for potential moderating variables such as organizational culture, which Bozkus, K. (2024) demonstrated can explain up to 40% of variance in technology implementation success. Finally, while the regression analyses establish associations between variables, they cannot definitively prove causal relationships due to the study's design limitations.

Future Research Directions

Future research should focus on conducting longitudinal studies to examine how relationships between technology adoption, training, organizational support, and performance evolve through different stages of digital transformation, an approach supported by Michelotto, F., & Joia, L. A. (2024) sociometrical perspective that revealed significant variations in technology effects across implementation phases. Researchers should develop more precise measurements of the constructs identified as significant in this study (particularly EP1, EP2, EP4, TCTA2, TCTA4, OS2, OS4, EPOP1, EPOP2, and EPOP4), building on Hoang, Dinh V., et al. (2025) framework for digital capability measurement that demonstrated improved predictive validity. Complementing quantitative findings with qualitative research through case studies would provide richer context, as demonstrated by Zhou, et, al., (2024) mixed-methods research that uncovered crucial implementation mechanisms invisible to purely quantitative approaches. Finally, examining factors that contribute to resistance to technology adoption addresses Sharma, R. (2024) research showing that technostress can reduce productivity gains from new technologies by up to 23% if not properly managed, providing more comprehensive guidance for organizations navigating digital transformation.

Authors Contributions
Conceptualization, Methodology, Results, Writing—original draft, N. R., Results, Writing draft, S.P.C., Discussion, Conclusion, Review, J.R.

Conflicts of Interest
The authors declare no conflict of interest.

References

[1] Al-Ababneh, H., Borisova, V., Zakharzhevska, A., Tkachenko, P., & Andrusiak, N. (2023). Performance of artificial intelligence technologies in banking institutions. WSEAS Transactions on Business and Economics, 20, 307–317.

[2] Anagnoste, S., Biclesanu, I., D'Ascenzo, F., & Savastano, M. (2021). The role of chatbots in end-to-end intelligent automation and future employment dynamics. In Springer Proceedings in Business and Economics (pp. 287–302). Springer.

[3] Araujo, T., Van Zoonen, W., & Ter Hoeven, C. (2022). "A large playground": Examining the current state and implications of conversational agent adoption in organizations. International Journal of Innovation and Technology Management, 19(7), 2250024. https://doi.org/10.1142/S0219877022500249.

[4] Ahmed, I., Asim, Z., Kamran, H., & Usman, A. (2022). Enabling organizational use of artificial intelligence: An employee perspective. Journal of Asia Business Studies, 16(2), 245–266. https://doi.org/10.1108/JABS-09-2020-0372.

[5] Baham, C., & Hirschheim, R. (2022). Issues, challenges, and a proposed theoretical core of agile software development research. Information Systems Journal, 32(1), 103–129. https://doi.org/10.1111/isj.12336.

[6] Bandura, A., & National Inst of Mental Health. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall, Inc.

[7] Bankins, S., et. al., (2023). A multilevel review of artificial intelligence in organizations: Implications for organizational behavior research and practice. Journal of Organizational Behavior. Advance online publication

[8] Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management, 17(1), 99-120. https://doi.org/10.1177/014920639101700108

[9] Becker, G., 1964. Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education, First Edition. NBER, Inc. available at, https://www.nber.org/books-and-chapters/human-capital-theoretical-and-empirical-analysis-special-reference-education-first-edition

[10] Bentler, P., and C. Chou. 1987. "Practical Issues in Structural Equation Modeling." Sociological Methods & Research 16: 78–117.

[11] Bialkova, S. (2023). How to optimise interaction with chatbots? Key parameters emerging from actual application. International Journal of Human-Computer Interaction.

[12] Bonekamp, L., & Sure, M. (2015). Consequences of industry 4.0 on Human Labour and Work Organisation. Journal of Business and Media Psychology, 6(1), 33–40. https://journal-bmp.de/wp-content/uploads/04_Bonekamp-Sure_final.pdf(open in a new window

[13] Bozkus, K. (2024). Organizational Culture Change and Technology: Navigating the Digital Transformation. IntechOpen. doi: 10.5772/intechopen.112903

[14] Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W.W. Norton & Company.

[15] calibration, and empirical study on its impact on organizational creativity and firm performance.

[16] Cascio, W. F., & Montealegre, R. (2016). How technology is changing work and organizations. Annual Review of Organizational Psychology and Organizational Behavior, 3(1), 349–375. https://doi.org/10.1146/annurev-orgpsych-041015-062352

[17] Chandar, P., Khazaeni, Y., Davis, M., Muller, M., Crasso, M., Liao, Q. V., Shami, N. S., & Geyer, W. (2017). Leveraging conversational systems to assist new hires during onboarding. In Lecture Notes in Computer Science, 10514, 381–391.

[18] Chen, B., Wu, Z., & Zhao, R. (2023). From fiction to fact: The growing role of generative AI in business and finance. Journal of Chinese Economic and Business Studies, 21, 471–496.

[19] Chithra Apoorva, D. A., & Brahmananda, S. H. (2020). A future research scope: Survey on an artificial interactive agent. International Journal of Advanced Science and Technology, 29, 6158–6166.

[20] Chow, Nathan C., and I Yeh (2022) "Correlation Between Learning Motivation and Satisfaction in Synchronous On-the-Job Online Training in the Public Sector." Frontiers in Psychology, vol. 13, p. 789252, https://doi.org/10.3389/fpsyg.2022.789252

[21] Colace, F., De Santo, M., Pascale, F., Lemma, S., & Lombardi, M. (2017). BotWheels: A petri net based chatbot for recommending tires. In Proceedings of the 6th International Conference on Data Science, Technology and Applications (DATA 2017) (pp. 350–358). Madrid, Spain.

[22] Dabbous, A., Aoun Barakat, K., & Merhej Sayegh, M. (2022). Enabling organizational use of

[23] Davenport, T. H. (2018). The AI advantage: How to put the artificial intelligence revolution to work. MIT Press.

[24] Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319–340. https://doi.org/10.2307/249008

[25] El Baroudi, S., Abdulaal, D.Y. and Rampur, M. (2018), "Training effectiveness during technological changes in Dubai-based companies: perspectives from managers and employees", Development and Learning in Organizations, Vol. 32 No. 3, pp. 1-3. https://doi.org/10.1108/DLO-10-2017-0085

[26] Fan, H., Gao, W., & Han, B. (2023). Are AI chatbots a cure-all? The relative effectiveness of chatbot ambidexterity in crafting hedonic and cognitive smart experiences. Journal of Business Research, 156, 113526.

[27] Fornell, C., and D. F. Larcker. 1981. “Structural Equation Models With Unobservable Variables and Measurement Error: Algebra and Statistics.” Journal of Marketing Research 18, no. 3: 382–388. https://doi.org/10.1177/002224378101800313.

[28] Goodhue, D.L., Thompson, R.L., 1995. Task-Technology Fit and Individual Performance. MIS Q. 19 (2), 213. https://doi.org/10.2307/249689.

[29] Gupta, S., Bostrom, R., 2009. Technology-Mediated Learning: A Comprehensive Theoretical Model. J. Assoc. Inf. Syst. 10 (9), 686–714. https://doi.org/10.17705/1jais.00207.

[30] Hair, J. F., W. C. Black, B. J. Babin, R. E. Anderson, and R. L. Tatham. (2010). Multivariate Data Analysis. 7th Ed. New York: Pearson.

[31] Hanaysha, J., 2016. Improving employee productivity through work engagement: Evidence from higher education sector. Manag. Sci. Lett. 6, 61–70. https://doi.org/10.5267/j.msl.2015.11.006.

[32] Hasan, Md. T., et al. (2021). COVID-19 in Bangladesh: An Especially Difficult Time for an Invisible Population. Disability & Society, 36, 1362-1367. https://doi.org/10.1080/09687599.2021.1929080.

[33] Hilkenmeier, F., Fechtelpeter, C., & Decius, J. (2021). How to foster innovation in SMEs: Evidence of the effectiveness of a project-based technology transfer approach. The Journal of Technology Transfer. https://doi.org/10.1007/s10961-021-09913-x

[34] Hoang, Dinh V., et al. (2025) "Digital Capabilities and Sustainable Competitive Advantages: The Case of Emerging Market Manufacturing SMEs." SAGE Open, https://doi.org/10.1177/21582440251329967.

[35] Hoogland, J. J., and A. Boomsma. 1998. “Robustness Studies in Covariance Structure Modeling: An Overview and a Meta-Analysis.” Sociological Methods & Research 26, no. 3: 329–367. https://doi.org/10.1177/0049124198026003003.

[36] Hsu, C.-L., & Lin, J. C.-C. (2023). Understanding the user satisfaction and loyalty of customer service chatbots. Journal of Retailing and Consumer Services, 71, 103211.
[37] Hung, P. D., Trang, D. T., & Khai, T. (2021). Integrating chatbot and RPA into enterprise applications based on open, flexible and extensible platforms. In Lecture Notes in Computer Science, 12983, 183–194.
[38] Ibdayanti, D. R., Oktaviani, C. Z., & Husin, S. (2024). Multiple regression analysis to the influence of communication management on project success. E3S Web of Conferences, 476, 01001. https://doi.org/10.1051/e3sconf/202447601001
[39] Illescas, C., Ortega, T., & Jadán-Guerrero, J. (2023). Gender bias in chatbots and its programming. Smart Innovation, Systems and Technologies, 337, 481–489.
[40] Inf. Manag. 58 (3), 103434. https://doi.org/ 10.1016/j.im.2021.103434.
[41] Jaiswal, A., Arun, C.J., Varma, A., 2022. Rebooting employees: upskilling for artificial intelligence in multinational corporations. Int. J. Hum. Resour. Manag. 33 (6), 1179–1208. https://doi.org/10.1080/09585192.2021.1891114.
[42] Johnson, C., Smith, D., & Brown, K. (2020). The impact of online learning communities on educational socialization: Exploring different dimensions of interaction in the International Development Institute. Open Journal of Social Sciences, *8*(1), 1–17.
[43] Kane, G. C., Phillips, A. N., Copulsky, J., & Andrus, G. (2021). The technology fallacy: How people are the real key to digital transformation. MIT Press.
[44] Kar, A. K., & Kushwaha, A. K. (2023). Facilitators and barriers of artificial intelligence adoption in business—Insights from opinions using big data analytics. Information Systems Frontiers, 25, 1351–1374.
[45] Kauffeld, S. (2016). Sustainable human resources development and training: Developing company seminars and training, measuring success, ensuring transfer. Springer.
[46] Kenny S, Victoria, 2019. "Employee productivity and organizational performance: A theoretical perspective," MPRA Paper 93294, University Library of Munich, Germany.
[47] Kim, Donggyu, and Yang Lee (2022). "R&D Employee Training, the Stock of Technological Knowledge, and R&D Productivity." R&D Management, vol. 52, no. 5, pp. 801-819, https://doi.org/10.1111/radm.12521
[48] Klassen, A. (2019). Deconstructing Paper-Lined Cubicles: Digital Literacy and Information Technology Resources in the Workplace. International Journal of Advanced Corporate Learning (iJAC), 12(3), pp. 5–13. https://doi.org/10.3991/ijac.v12i3.11170
[49] Kraiger, K., & Ford, J. K. (2021). The science of workplace instruction: Learning and development applied to work. Annual Review of Organizational Psychology and Organizational Behavior, 8(1), 45–72. https://doi.org/10.1146/annurev-orgpsych-012420-060109
[50] Lake, S. (2000). Low Cost Strategies for Employee Retention: Compensation and Benefits Review. 32(4),65-72.
[51] Lappeman, J., Marlie, S., Johnson, T., & Poggenpoel, S. (2023). Trust and digital privacy: Willingness to disclose personal information to banking chatbot services. Journal of Financial Services Marketing, 28, 337–357.
[52] Leadership insight (2013).Employee engagement; maximizing organizational performance. The right management Power Company. Right Management Company
[53] Lee, Y., Kozar, K., & Larsen, K. (2003). The Technology Acceptance Model: Past, Present, and Future. Communications of the Association for Information Systems, 12, pp-pp. https://doi.org/10.17705/1CAIS.01250
[54] Leo John, R. J., Potti, N., & Patel, J. M. (2017). Ava: From data to insights through conversation. In Proceedings of the CIDR 2017—8th Biennial Conference on Innovative Data Systems Research. Chaminade, CA, USA.
[55] Lytovchenko, I., Terenko, O., Lavrysh, Y., Ogienko, O., Avsheniuk, N., & Lukianenko, V. (2022). Training Delivery Methods Implemented by American Companies: Opportunities and Challenges in Context of Knowledge Society. Postmodern Openings, 13(4), 187-198. https://doi.org/10.18662/po/13.4/513

[56] Makhija, P., & Chacko, E. (2021). Efficiency and advancement of Pearson Education in service sector with special reference to banking industry. In Fourth Industrial Revolution and Business Dynamics: Issues and Implications (pp. 21–35). Springer.

[57] Mardiatmoko, G. (2020). PENTINGNYA UJI ASUMSI KLASIK PADA ANALISIS REGRESI LINIER BERGANDA (STUDI KASUS PENYUSUNAN PERSAMAAN ALLOMETRIK KENARI MUDA [CANARIUM INDICUM L.]). BAREKENG: Jurnal Ilmu Matematika Dan Terapan, 14(3), 333-342. https://doi.org/10.30598/barekengvol14iss3pp333-342

[58] Mathis, Robert, L., & John, H. J. (2003).Human Resource Management. (11th ed).Mason, OH:Thomson/South-Western.

[59] McNamara, C. (2005). Field Guide to Leadership and Supervision for Nonprofit Staff.(2nd ed.).Amazon.

[60] Mehrolia, S., Alagarsamy, S., & Moorthy, V. (2023). Will users continue using banking chatbots? The moderating role of perceived risk. FIIB Business Review.

[61] Michelotto, F., & Joia, L. A. (2024). Organizational Digital Transformation Readiness: An Exploratory Investigation. Journal of Theoretical and Applied Electronic Commerce Research, 19(4), 3283-3304. https://doi.org/10.3390/jtaer19040159

[62] Mikalef, P., Gupta, M., 2021. Artificial intelligence capability: Conceptualization, measurement

[63] Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S.O., Torvatn, H.Y., Gupta, M., Niehaves, B., 2023. Examining how AI capabilities can foster organizational performance in public organizations. Gov. Inf. Q. 40 (2), 101797. https://doi.org/10.1016/j.giq.2022.101797.

[64] Mohammad Kashef, S. (2023). A Scrutiny of the Role of Knowledge Management in Employees' Organizational Culture, Motivation, and Success. IntechOpen. doi: 10.5772/intechopen.1002306

[65] Nunnally, J. 1978. Psychometric Theory. New York: McGraw-Hill. https://doi.org/10.1037/018882.

[66] Paul, Justin, et al.(2024) "Digital Transformation: A Multidisciplinary Perspective and Future Research Agenda." International Journal of Consumer Studies, vol. 48, no. 2, p. e13015. https://doi.org/10.1111/ijcs.13015.

[67] Pillai, R., & Sivathanu, B. (2020). Adoption of artificial intelligence (AI) for talent acquisition in IT/ITeS organizations. Benchmarking: An International Journal, 27(9), 2599–2629. https://doi.org/10.1108/BIJ-04-2020-0186

[68] Piyatumrong, A., Sangkeettrakarn, C., Witdumrong, S., & Cherdgone, J. (2018). Chatbot technology adaptation to reduce the information gap in RD center: A case study of an IT research organization. In Proceedings of the Portland International Conference on Management of Engineering and Technology (PICMET) (pp. 19–23). Honolulu, HI, USA.

[69] Raja, A. G. K., Furqan, A. K. & Muhammad, A. K. (2011). Impact of training and development on organizational performance". Global Journal of Management and Business Research. 11(7), 1-7.

[70] Richter, S., Kortsch, T., & Kauffeld, S. (2020). Understanding learning spillover: The major role of reflection in the formal-informal learning interaction within different cultural value settings. Journal of Workplace Learning, 32(7), 513–532. https://doi.org/10.1108/JWL-01-2020-0008

[71] Russell, S., & Norvig, P. (2015). Artificial Intelligence: A Modern Approach. Pearson Education.

[72] Saengrith, W., Viriyavejakul, C., & Pimdee, P. (2022). Problem-based blended training via chatbot to enhance the problem-solving skill in the workplace. Emerging Science Journal, 6, 1–12.

[73] Schaeffer, E. (2017). Industry X.0: Realizing digital value in industrial sectors. Redline.

[74] Sharma, R. (2024). Technostress In The Digital World And Impact On Employee Work Performance And Mental Health. Journal of Business Management and Information Systems, 11(2), 64–73. https://doi.org/10.48001/jbmis.1102005

[75] Silva, S. C., De Cicco, R., Vlacic, B., & Elmashhara, M. G. (2023). Using chatbots in e-retailing—How to mitigate perceived risk and enhance the flow experience. International Journal of Retail & Distribution Management, 51, 285–305.

[76] Steinbauer, F., Kern, R., & Kröll, M. (2019). Chatbots assisting German business management applications. In Lecture Notes in Computer Science, 11606, 717–729.

[77] Straber, T., & Axmann, B. (2021). Analysis and evaluation of AI applications in logistics. Logistics Journal, 2021.

[78] Sung, Sun Y., and Jin N. Choi. (2014). "Do Organizations Spend Wisely on Employees? Effects of Training and Development Investments on Learning and Innovation in Organizations." Journal of Organizational Behavior, vol. 35, no. 3, pp. 393-412, https://doi.org/10.1002/job.1897.

[79] Surujlal, J., & Singh, P. (2003). Human resources management of professional sport coaches in South Africa. African Journal for Physical, Health Education, Recreation and Dance, Special Edition, 50–58.

[80] Suyono (2015), Analisis Regresi untuk Penelitian. Yogyakarta: Deepublish.

[81] Tarafdar, M., Cooper, C. L., & Stich, J.-F. (2019). The technostress trifecta—techno eustress, techno distress and design: Theoretical directions and an agenda for research. *Information Systems Journal, 29*(1), 6–42. https://doi.org/10.1111/isj.12169.

[82] Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412.

[83] Virkar, M., Honmane, V., & Rao, S. U. (2019). Humanizing the chatbot with semantics based natural language generation. In Proceedings of the 2019 International Conference on Intelligent Computing and Control Systems (ICCS 2019) (pp. 891–894). Madurai, India.

[84] Walkowiak, E. (2023). Task-interdependencies between generative AI and workers. Economics Letters, 231, 111315.

[85] Wang, B. (2018) 'Digital Work and High-Tech Wanderers: Three Theoretical Framings and a Research Agenda for Digital Nomadism', in . Australasian Conference on Information Systems (ed.), Sydney: UTS ePRESS. Available at: https://doi.org/10.5130/acis2018.bl.

[86] Westerman, G., Bonnet, D., & McAfee, A. (2019). Leading digital: Turning technology into business transformation (2nd ed.). Harvard Business Review Press.

[87] Wijayati, D.T., Rahman, Z., Fahrullah, A., Rahman, M.F.W., Arifah, I.D.C., Kautsar, A., 2022. A study of artificial intelligence on employee performance and work engagement: the moderating role of change leadership. Int. J. Manpow. 43 (2), 486–512. https://doi.org/10.1108/IJM-07-2021-0423.

[88] Xu, Q., Yan, J., & Cao, C. (2022). Emotional communication between chatbots and users: An empirical study on online customer service system. In Lecture Notes in Computer Science, 13336, 513–530.

[89] Zhou, Q., Yu, H., Adams, K., Attah-Boakye, R., & Johansson, J. (2024) Uncovering the impact of digital technologies on strategising: evidence from a systematic literature review. International Journal of Management Reviews, 1–23. https://doi.org/10.1111/ijmr.12387