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AN EVALUATION OF INDUSTRY 4.0 TECHNOLOGIES AND RESOURCE MANAGEMENT IN NIGERIAN FOOD MANUFACTURING FIRMS

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Abstract

Industry 4.0 technology could improve resource management in Nigeria's food manufacturing sector, improving efficiency, quality, and sustainability. This study examines the use and impact of these technologies in selected food manufacturing enterprises in Ilorin, Kwara State, using data from 181 respondents from various departments. Results show that Industry 4.0 technologies explain 22.3% of resource storage variance (R^2 = 0.223) and 8.0% of resource allocation variance (R^2 = 0.080), indicating low adoption and integration. Big Data Analytics (β = 0.347, P = 0.000) and Cyber-Physical Systems (CPS) (β = 0.290, P = 0.002) significantly contributed to resource storage, while Additive Manufacturing (3D Printing) (β = 0.191, P = 0.047) was the only significant contributor to resource allocation. Despite these favourable results, labour training and infrastructural readiness deficiencies limited the effect of AI, VR, and robotics. The study indicates that

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targeted training, strategic technology alignment, and infrastructure improvements are necessary to properly leverage Industry 4.0 in resource management. These findings suggest that Nigeria's food manufacturing sector needs better implementation strategies to integrate Industry 4.0 technologies.

Introduction

Background to the Study

Industry 4.0 offers Nigerians possibilities and problems. Infrastructure, digital literacy, and legal frameworks are challenges as the country digitises and advances. Industry 4.0 technologies are helping Kwara State companies like Olam Ilorin boost competitiveness, efficiency, and sustainability (Nwankwo et al., 2021; Aremu & Adepoju, 2020). The late 18th and early 19th century Industrial Revolution brought tremendous economic, technological, and social transformation (Vries, 2008; Mohajan, 2019). It signalled the global shift from agrarian and artisan economies to industrial and machine-based industry, including Nigeria. The revolution altered lifestyles and work (Chete et al., 2014).

Industry 4.0, coined by the German government in 2011, leverages automation and computerisation to create "smart factories" that use cyber-physical systems, the IoT, and AI to improve operations and productivity (Kagermann et al., 2013; Schwab, 2020). Industry 4.0 technologies promise to boost production, efficiency, and competitiveness (Thames & Schaefer, 2017). Several Nigerian sectors want to use Industry 4.0 to innovate and improve efficiency (Chete et al., 2014). Nigerian Industry 4.0 technology may affect manufacturing, agribusiness, energy, healthcare, logistics and supply chain, and education.

Despite these benefits, food sector resource management is difficult, requiring efficient use of resources, energy, water, and other inputs across the supply chain. Raw material sourcing, energy, water, supply chain complexity, regulatory compliance, technological adoption, and changing consumer expectations are challenges (Miranda et al., 2019; Salem, 2022). Evaluation of industry 4.0 technology adoption in Ilorin, Kwara State, Nigeria food manufacturing enterprises is needed.

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Statement of the Problem

Industry 4.0 can improve food manufacturing efficiency, quality, and sustainability. Many Nigerian companies struggle to integrate sophisticated technologies. Some companies employ new technologies without a strategy, which fails to achieve projected benefits. According to empirical studies (Fosso Wamba et al., 2019), Industry 4.0 technologies must be aligned with organisational structures, worker dynamics, and technology infrastructure.

Industry 4.0's practical effects in Nigeria, especially in resource-intensive areas like food processing, are poorly studied. Studies show that emerging economies lack awareness of how these technologies affect resource management and operational efficiency (Akpan-Obong & Nkanga, 2020). Additional socio-economic and institutional elements unique to Nigeria may affect the acceptance and success of these innovations (Ajayi & Olaoye, 2018). This study aims to address these gaps by examining the impact of Industry 4.0 technologies on resource management in selected food manufacturing firms in Ilorin, Kwara State, Nigeria. It investigates the extent of technology adoption and its effects on resource ordering, storage, and allocation.

Research Questions

This study answered the following research questions:

i. What is the effect of industry 4.0 technologies on resource storage in the study area?
ii. What is the effect of industry 4.0 technologies on resource allocation in the study area?

Objectives of the Study

The general objective of the study is to assess the effect of industry 4.0 technologies on resource management within selected manufacturing firms in Ilorin, Kwara State. While the specific objectives are to:

i. examine the effect of industry 4.0 technologies on resource storage in the study area; and
ii. examine the effect of industry 4.0 technologies on resource allocation in the study area.

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Scope of the Study

This study examines how Industry 4.0 technologies affect resource management in selected food manufacturers in Ilorin, Kwara State, Nigeria. It examines how IoT, AI, robotics, data analytics, and automation manage human, material, financial, energy, and time resources in the manufacturing value chain. The study studies important food manufacturing enterprises in Ilorin, Kwara State to provide localised insights into Industry 4.0 deployment.

LITERATURE REVIEW

Concept of Industry 4.0 Technology

Mechanisation of Production, Urbanisation, Factory System, Transportation Revolution, Technological Innovations, Significant changes in social structures, labour relations, and living conditions, Economic Transformations, Social Movements and Calls for Reforms, and Global Impact are key features of Industrial Revolution. Sharma & Singh (2020) noted that the Industrial Revolution has had multiple phases, each distinguished by technology advances and manufacturing process changes. Industry 1.0 to Industry 4.0 reflect different stages in industry and technological evolution (Tools, 2018; Koc & Teker, 2019). Industrial Revolution 1.0 occurred in the late 18th to mid-19th century. The invention of water wheels and steam engines revolutionised manufacturing (Sharma & Singh, 2020).

The mechanisation of textile, coal mining, iron production, and mostly traditional food manufacture marked the worldwide and Nigerian change from rural to industrial economies. Industry 2.0 dates from the late 19th to early 20th century. Global assembly lines and electricity utilisation were present (Mohajan, 2019). Mass production, like Thomas Edison's light bulb and Henry Ford's assembly line, increased efficiency and reduced costs. Massive industrial corporations arose. Few major food manufacturing facilities emerged in Nigeria during this time (Chete et al., 2014).

Industry 3.0 introduced electronic systems, PLCs, and broad computer use in production in the mid-20th to late 20th century (Chaudhari, 2021). Robotics reduced human labour. This phase relied on IT (Kumar et al., 2019). Nigeria's food manufacturing sector improved efficiency and precision. Automation and electronics improved processing (Onibonoje et al., 2021).

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Industrial revolution 4.0 began in the late 20th century. It unites digital, physical, and biological technology (Moll, 2021). Javaid et al. (2021) said networking, data analytics, AI, and the IoT drive it. Smart factories use cyber-physical systems for real-time data interchange and intelligent decision-making, improving efficiency, customisation, and sustainability, according to Yao et al. (2019). Industry 4.0 seeks efficient, adaptable, and customer-responsive smart factories (Kumar et al., 2019; Yao et al., 2019; Ahmadi, 2020).

Concepts of Resource Management

Resource management efficiency and optimisation are crucial for today's competitive businesses. Resource management optimises efficiency and production by strategically allocating and using resources. These resources include human capital, financial assets, raw commodities, and technology. Efficient resource management starts with finding and buying the resources needed to achieve organisational goals. Assessing present demands, projecting future needs, and strategically acquiring resources to meet demand. To maximise operational success, these resources must be deployed well.

Resource management involves optimising resource use to maximise efficiency. This requires optimising workflows, eliminating bottlenecks, and reducing waste across the company. Organisations can boost productivity and performance by optimising resource use. For instance, Hussain et al. (2021) stress resource management strategies for project success. Their study shows how resource allocation and use improve project efficiency and success. Simchi-Levi et al. (2020) examine logistics logic and supply chain optimisation. Their research shows that resource allocation optimisation can save money, improve customer satisfaction, and boost competitiveness. Efficient resource management allows businesses to prioritise, allocate, and deploy resources. Organisations must apply efficient resource management strategies to streamline workflows, optimise resource utilisation, and boost productivity in today's dynamic business environment. Companies can boost productivity, workflow, and resource utilisation by using efficient resource management.

Companies must follow these strategies to stay competitive in today's business environment. This theory explains resource management efficiency and optimisation, supported by Hussain et al. (2021) and Simchi-Levi et al. (2020), which show their importance in organisational performance.

Asset managers use data analytics and machine learning algorithms to predict equipment problems and schedule repairs. This differs from reactive maintenance, which restores equipment after failure, causing costly downtime and productivity losses. Through real-time equipment monitoring and historical data analysis, businesses can spot patterns and anomalies that may suggest breakdowns or deterioration.

This predictive capability lets maintenance teams prevent critical breakdowns by intervening early. Downtime is reduced, asset lifespan is optimised, and maintenance expenses are reduced. Li et al. (2021) study manufacturing system predictive maintenance. They study predictive maintenance methods and their applications, emphasising early fault identification and intervention. Jardine and Tsang (2020) explore maintenance ideas and practises, highlighting predictive solutions to optimise asset reliability and performance. Predictive maintenance requires a robust data gathering, storage, and analysis infrastructure and advanced analytics to gain insights.

Companies need sensors, IoT devices, and condition monitoring systems to collect real-time equipment data. Additionally, machine learning systems evaluate this data, identify failure trends, and develop predictive maintenance schedules. Predictive maintenance helps companies move from reactive to proactive maintenance, improving equipment durability, downtime, and operational efficiency. Predictive maintenance is a paradigm change in asset management that unlocks productivity and competitiveness. Li et al. (2021) and Jardine & Tsang (2020) emphasise predictive maintenance's role in asset reliability and downtime reduction.

Concepts of Automation in Food Manufacturing Industry

Improvements and prospects Automation is revolutionising Nigeria's food production sector, a crucial economic engine. These technologies are improving production efficiency, quality, and sector competitiveness. (Chui et al., 2017; Duong, 2020). Nigerian food manufacturers make dairy, confections, drinks, and processed foods (Ojinnaka, 2011). However, Ojinnaka (2011) observed that the sector faced issues such human labour, product quality, and efficiency. Automation can overcome these challenges and bring the sector up to worldwide standards, according to several authors (Ojinnaka, 2011; Talaviya et al., 2020; Dinrifo, 2022).

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Automated manufacturing lines using robotic arms for packaging, labelling, and palletising ensure product homogeneity, speed up processes, and reduce manual work (Wakchaure et al., 2023). Agriculture robots with advanced visual systems grade and sort produce consistently. Fresh product-dependent industries benefit most from this. Robots with improved sensing and visual systems do quality control (Tian et al., 2020). These technologies detect faults, stains, and quality differences (Jha et al., 2019). Robotic systems and AGVs simplify industrial material handling and logistics (Guma, 2021).

Automation and robotics can improve productivity, produce more food items for export, maintain product quality, improve worker efficiency and safety, reduce operating costs, and reduce waste (Guma, 2021; Çiğdem et al., 2023). The Nigerian food industry faces many challenges in automating and using robots (Dinrifo et al., 2022). These include the initial investment, personnel retraining, and integrating new automation technology with existing infrastructure (Dinrifo et al., 2022; Li, 2022).

Funding, government incentives, training, and management changes can overcome these difficulties (Idoko, 2023). Automation and robotics in Nigerian food manufacturing represent a major step towards modernisation and competitiveness (Bayo & Onyenma, 2019; Hassoun et al., 2023). Strategic planning, talent development, and government-private sector partnership are needed to help the industry adopt these technologies and grow (Talaviya et al., 2020; Uba, 2023).

Theoretical Review

Resource Base Theory:

For sustainable and profitable operations, food manufacturers must efficiently use raw resources, energy, and labour. Effective resource management optimises productivity, addresses environmental issues, and meets regulations (Okokpujie & Tartibu, 2023). Food production resources are controlled in numerous ways. Raw materials, energy, manpower, wastewater management, and technological integrations are included. Raw material management optimises inventory levels to satisfy production demands and reduce excess stock (Ozturk, 2020). Supply chain-integrated forecasting technologies improve demand estimates and inventory planning (Karki, 2024).

Well-trained staff boosts production and efficiency. Workforce management systems optimise labour use, matching staffing levels to production needs. Predictive analytics can predict labour needs and schedule shifts (Kareska, 2023; Gomathi et al., 2023; Omar, 2019). ERP systems that integrate inventory, production schedules, and workforce management. Real-time data integration improves operational efficiency and decision-making (Gupta & Kohli, 2006; Zhao & Tu, 2021).

METHODOLOGY

In achieving the objectives of the study, a descriptive survey method was employed. This design was chosen because it allows for the collection of detailed information from a sample of individuals that is representative of a larger population. It is particularly suitable for understanding the adoption and effect of Industry 4.0 technologies in resource management within the selected food manufacturing firms in Ilorin, Kwara State, Nigeria. The data was obtained using questionnaire to collect data.

The population for this study involves the employees of selected food manufacturing firms in Ilorin, Kwara State, Nigeria. The workforce in the Ilorin facility consists of various departments essential for smooth operations and maintaining high standards in production process. The departments typically include production, quality assurance, logistics, maintenance, human resources, finance, administration etc. The total number of permanent staff in firms selected includes approximately 332 employees, with additional support staff contributing to daily operations.

TABLE 3.1: Population Distribution of Selected Food Manufacturing Firms, Ilorin, Kwara State.

Departments	Firm A	Firm B	Population
Production/Operations Department	26	47	73
Information Technology (IT) Department	8	10	18
Supply Chain and Logistics Department	28	36	64
Quality Control/Assurance Department	27	46	73
Human Resources Department	7	9	16
Maintenance and Engineering Department	28	48	76
Finance Department	5	7	12
Total	**129**	**203**	**332**

Source: Field Survey, 2024

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Sample and Sampling Technique for the Study: A sample is a tiny representation of a bigger population. To be utilised as a representative sample of a population, a group or a restricted set of items must be chosen from the population. The sample size of the study was selected from staff of the selected Food Industries. The participants included staff members from the following departments: finance, information technology, supply chain and logistics, quality control and assurance, research and development (R&D), human resources, maintenance and engineering, and production/operations. In determining the sample size, both purposive sampling and judgmental sampling was used in selecting the people that are relevant into the study. Purposive sampling is a non-probability sampling technique in which the researcher's select respondents who are relevant to the study and whose judgement is important to the study. In judgmental sampling, the researcher relies on their judgement or expertise to select participants who they believe will best serve the research purpose.

The eight departments within the organisation were given equal chances involving both top management level to lower management level. A total of 332 staff were selected from various departments.

The sample size for the study was determined using the Yamane sample size formula formulated by Wang and Cheung (2011).

The formula stated in Equation (3.1) was used to estimate the sample size as follows:

$$n = \frac{N}{1+N(e)^2} \qquad (3.1)$$

where;

n = sample size, N= Total Population,

e= Acceptable error limit (0.05) and 1 is Unity (it is constant).

Substituting the 332 population size of selected firms and an acceptable error limit of 0.05 into the equation we have:

$$n = \frac{332}{1 + 332(0.05)^2}$$

$$n = \frac{332}{1.83}$$

n = 181

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Therefore, the sample size considered for state government firm in order to achieve the stated objectives of this study is 181.

Method of Data Analysis: The data collected was well analysed with both descriptive and referential statistics such as frequency Tables, per centages, mean and standard deviations, Regression Analysis and Analysis of Variance (ANOVA).

RESULTS AND DISCUSSION

This chapter entails the data analysis and interpretation of the findings from the study, industry 4.0 technology adoption and resource management in selected manufacturing firms in Ilorin, Kwara State, Nigeria. It comprises of response rate of questionnaire, data coding and sorting, demographic characteristics of respondents and interpretation and discussion of the study objectives and research hypothesis.

Response Rate of Questionnaire

Table 4.1 Response Rate of Questionnaire

Copies of Questionnaire	Respondents	
	Frequency	Percent
Quantity Distributed	181	100.0
Quantity Retrieved	145	80.1
Quantity Analysed after Data Sorting	139	76.8

Source: Field Survey, 2024

Effect of Industry 4.0 Technologies on Resource Storage

The result from regression analysis is shown in table 4.2. The R^2 value of 0.223 under model summary indicates that the industry 4.0 technologies explain 22.3% of variance in resource storage in the study area. This interprets that resource storage is just 22.3% effective given the prevailing usage of industry 4.0 technologies in the study area. Furthermore, the significant column (Sig.) under the coefficient table presents the significance of each of the constructs of industry 4.0 technologies on resource storage in the study area. Similarly, just in the case of resource ordering in table 4.2 above, the constructs, big data analytics, cyber-physical systems, and manufacturing additive (3D printing) are significant with P-values 0.000, 0.002 and 0.036 respectively. However, other

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constructs of industry 4.0 technologies understudy are insignificant with P-values above 0.005

The standardized beta value gives the relative contribution of industry 4.0 technologies vis-à-vis resource storage. "Big data analytics" has the highest contribution (β = 0.347) relative to the dependent variable (resource storage). This is seconded by "cyber-physical systems" and "additive manufacturing" with a standardized beta (β) values 0.290 and 0.185 respectively. This interprets that the usage of big data analytics, additive manufacturing (3D-printing) and cyber-physical systems still remain very much impactful over other industry 4.0 technologies with regards to resource ordering. This is evident in optimized space utilization, real time monitoring of inventory level and storage conditions and enhanced coordination between resource ordering and storage. This supports Ozturk (2020) that RFID tags, GPS-enabled devices, and IoT sensors track raw materials, ingredients, and final goods along the supply chain (Maqbool et al., 2022). Visibility improves inventory management and reduces stockouts and overstocks. Automation and robotics, virtual reality, and artificial intelligence have unstandardised negative beta values of -0.035, -0.055, and -0.019, indicating that resource storage would plummet with their use. This indicates weak application and competency in automation, robotics, virtual reality, and AI in resource management, particularly resource storage in the studied region.

Maqbool et al. (2022) noted that Industry 4.0 technologies, particularly IoT, RFID, and GPS-enabled devices, improve inventory management and storage visibility and control. This supports the study's R^2 value, indicating a little yet significant impact of Industry 4.0 technology on resource storage. Tortorella et al. (2019) observed that while Industry 4.0 technologies boost efficiency, technological and operational limitations restrict their effects on storage processes, explaining 22.3% of variance. Zhang et al. (2020) found that big data improves resource storage by enabling real-time decision-making and eliminating inefficiencies. CPS is essential for real-time storage monitoring, inventory management, and waste reduction, according to Ivanov et al. (2019). On-demand manufacture with additive printing decreases storage space, according to Holmström et al. (2016). Ben-Ner & Siemsen (2017) recognised its storage benefits from inventory reduction and decentralised production.

Table 4.2 Effect of Industry 4.0 Technologies on Resource Ordering

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.472[a]	.223	.172	.36418

a. Predictors: (Constant), Additive Manufacturing (3D printing), Cyber-Physical Systems (CPS), Internet of Things (IoT), Augmented Reality (AR), Automation and Robotics , Artificial Intelligence (AI), Big Data Analytics, Virtual Reality (VR)

b. Dependent Variable: Resource Storage

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	3.243	.257		12.606	.000		
	Internet of Things (IoT)	-.037	.044	-.073	-.833	.406	.828	1.207
	Big Data Analytics	.146	.040	.347	3.674	**.000**	.713	1.403
	Automation and Robotics	-.035	.039	-.082	-.899	.370	.758	1.319
	Augmented Reality (AR)	.021	.037	.050	.565	.573	.798	1.254
	Virtual Reality (VR)	-.055	.037	-.145	-1.474	.143	.654	1.529
	Artificial Intelligence (AI)	-.019	.037	-.050	-.513	.609	.665	1.504
	Cyber-Physical Systems (CPS)	.117	.036	.290	3.206	**.002**	.779	1.284
	Additive Manufacturing (3D printing)	.081	.038	.185	2.115	.036	.833	1.200

a. Dependent Variable: Resource Storage

Effect of Industry 4.0 Technologies on Resource Allocation

Table 4.3 presents the model summary which shows R^2 values of 0.080. This indicates that the social dimension explains 8.0% variance in resource allocation. This means the current usage of industry 4.0 technologies contributes just 8.0% in resource allocation in the study area.

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Furthermore, the coefficient table presents the relative contribution of each of the constructs of industry 4.0 technologies on resource allocation in the study area. Column under significant (sig) shows the relative significance of constructs of industry 4.0 technologies with only "additive manufacturing (3D printing)" having significant P value 0.047 while other constructs have P- value above 0.05 hence insignificant. Furthermore, standardized beta value shows that "additive manufacturing (3Dprinting) has the greatest relative contribution with a beta value (β = 0.191). In the case of resource allocation, "big data analytics" and cyber-physical system were observed to have minute beta value (β) 0.096 and 0.093 respectively as against what beta value in resource ordering and resource storage above. This interprets that additive manufacturing contribute solely contribute significant towards resource allocation in the study area. This submission is upheld by unstandardized beta value 0.270 for additive manufacturing which indicates that resource allocation will be enhanced by 0.270 by every unit increase in additive manufacturing. Big data analytics and cyber-physical system having relatively lower unstandardized beta values of 0.130 and 0.121 respectively and also insignificant.

This contradicts Guma (2021), which found that industry 4.0 increased productivity and decreased physical labour, increased production to meet the country's growing food demand and exports, consistent product quality, worker efficiency and safety, lower operating costs, and less waste. The low R^2 value (8.0%) suggests that Industry 4.0 technologies play a limited impact in resource allocation in the research area. This supports Tortorella et al. (2019), who found that Industry 4.0 technologies' resource allocation effectiveness depends on their integration and maturity in organisational processes. According to Sanders et al. (2016), some Industry 4.0 technologies may have less direct impact on resource allocation but rather on operational efficiency. Guma (2021) found that Industry 4.0 technology increased production, reduced labour use, and optimised resource allocation. Comparing the research area's technological preparedness, worker capabilities, and sectoral applications may explain the disparity. These conclusions differ from Guma's, emphasising the need for Industry 4.0 deployment, training, and alignment with corporate goals.

Table 4.3: Effect of industry 4.0 technologies on Resource Allocation.

Model Summary[b]				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.282[a]	.080	.019	1.27686

a. Predictors: (Constant), Additive Manufacturing (3D printing), Cyber-Physical Systems (CPS), Internet of Things (IoT), Augmented Reality (AR), Automation and Robotics , Artificial Intelligence (AI), Big Data Analytics, Virtual Reality (VR)

b. Dependent Variable: Resource Allocation

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.493	.902		2.763	.007		
	Internet of Things (IoT)	.063	.155	.039	.407	.685	.828	1.207
	Big Data Analytics	.130	.139	.096	.936	.351	.713	1.403
	Automation and Robotics	.064	.137	.046	.463	.644	.758	1.319
	Augmented Reality (AR)	-.148	.129	-.112	-1.150	.252	.798	1.254
	Virtual Reality (VR)	.143	.130	.118	1.100	.273	.654	1.529
	Artificial Intelligence (AI)	-.141	.131	-.115	-1.076	.284	.665	1.504
	Cyber-Physical Systems (CPS)	.121	.128	.093	.945	.347	.779	1.284
	Additive Manufacturing (3D printing)	.270	.134	.191	2.009	.047	.833	1.200

a. Dependent Variable: Resource Allocation

CONCLUSION AND RECOMMENDATIONS

Conclusion

The following conclusions were drawn:

i. Limited adoption and impact of Industry 4.0 technologies in resource allocation was seen, with just 8.0% variance explained by these technologies. The lone substantial contributor, additive

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manufacturing, had a beta value of 0.191, highlighting its resource allocation efficiency. Big data analytics and CPS contributed little.

ii. General Remarks: Due to its adaptability, additive manufacturing continually improved resource ordering, storage, and allocation. Other Industry 4.0 technologies like AI, AR, VR, and automation have little influence due to implementation, training, and organisational needs and capability.

Recommendations

Following the outcomes of this study, the subsequent suggestions were put forward:

i. The organisation should provide adequate training for personnel in the study area to solve deficiencies in using ignored apps or build comprehensive programs to improve workforce competency in handling Industry 4.0 technologies.

ii. Encourage employees skilled in industry 4.0 technologies to upgrade to higher packages.

iii. Reduce acceptance hurdles for AI, AR, VR, and automation by improving training, capacity building, and customised implementation tactics.

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