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Artificial Intelligence (AI) adoption and organisational transformation of bakery firms in Port Harcourt, Rivers State

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Abstract
This study investigated the relationship between artificial intelligence adoption and organisational transformation of bakery firms in Port Harcourt, Rivers State. The study adopted the correlational research design. 100 managers from 20 selected and registered bakery firms operating in Port Harcourt was sued for the study. The questionnaire designed in a likert response options was used for the collection of data for the study. Pearson Product Moment Correlation (PPMC) was used to test the formulated hypotheses at 0.01 level of significance. Findings revealed that there is a positive significant relationship between artificial intelligence adoption (predictive maintenance and smart production scheduling) and organisational transformation (knowledge transfer and innovation) of bakery firms in Port Harcourt, Rivers State. The study concluded that artificial intelligence adoption transforms traditional bakery operations into knowledge-driven and innovative production systems. This transformation strengthens competitiveness and long-term sustainability of bakery firms. Among others, the study recommended that bakery firms should link AI maintenance systems to digital knowledge platforms where equipment data, fault reports, and repair solutions are stored and shared. This will enable technicians and production staff to access past experiences, learn best practices and transfer technical knowledge more effectively, thereby supporting organisational learning.

Keywords: Artificial ıntelligence adoption, organisational transformation, bakery firms, predictive maintenance, innovation

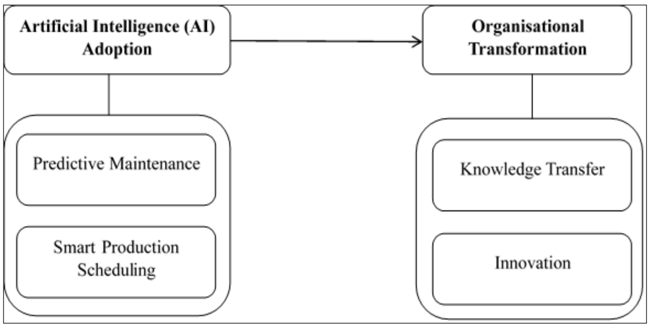
Introduction

Bakery firms in Port Harcourt operate in a competitive and resource-constrained environment where organisational transformation, among others, expressed through effective knowledge transfer and continuous innovation, has become central to sustaining performance and growth. Evidence from hospitality and manufacturing firms in Rivers State shows that systematic knowledge transfer significantly enhances organizational innovativeness, as employees share recipes, process know-how and customer insights that lead to new products and improved processes (Pepple, 2020; Edison, 2020) [10, 25]. Similarly, studies on confectionery and bakery SMEs in Nigeria indicate that innovation in process improvement and technology use is a key driver of superior business performance, but its benefits are often under-realised when firms lack structured mechanisms for learning and knowledge sharing (Abdulkazeem, 2025) [1]. In this context, artificial intelligence (AI) emerges as a strategic enabler that can reshape how bakery firms create, store, and apply knowledge for innovation.

Research on Nigerian enterprises shows that AI-enabled tools for data analytics, real-time information exchange, and collaborative platforms can substantially enhance knowledge sharing, decision-making, and organisational efficiency, particularly where traditional knowledge systems are fragmented (Ola-Oluwa, 2024; Abidemi, 2024) [2, 22]. Moreover, AI applications in manufacturing in Rivers State have been linked with higher innovation and cost reduction, demonstrating that intelligent technologies can support new ways of working and producing in local industrial settings (Bekuru & Nwinyokpugi, 2021) [5]. Within bakeries, AI-driven predictive maintenance can use sensor data from ovens, mixers, and refrigeration units to anticipate faults, reduce downtime, and stabilize product quality, thereby embedding new technical knowledge about equipment behaviour into daily operations (Stornelli *et al*., 2024) [29]. Likewise, smart production scheduling systems that analyse historical sales, weather patterns, and input availability can generate data-driven baking plans, reducing waste, aligning output with demand, and freeing managers to focus on creative product development and service innovations (Ola-Oluwa, 2024; Stornelli *et al*., 2024) [22, 29].

Studies of digital and AI adoption in Nigerian supply chains and enterprises further suggest that such technologies enhance agility, real-time monitoring, and data-driven decision-making, all of which underpin organisational transformation in dynamic markets (Omonzejele & Okogun, 2025; Aliu *et al*., 2025) [3, 23]. However, they also highlight contextual barriers—limited infrastructure, skills gaps, and resistance to change—that can constrain AI's transformative effect if not properly managed (Ola-Oluwa, 2024; Omonzejele & Okogun, 2025; Hassan, 2024) [14, 22, 23]. For bakery firms in Port Harcourt, where prior work has largely focused on procurement practices and process efficiency rather than advanced digital tools (Opuwari, 2024) [24], examining AI adoption through predictive maintenance and smart scheduling provides a timely lens for understanding how these small and medium businesses can deepen knowledge transfer, accelerate innovation, and achieve sustainable organisational transformation in Rivers State's evolving business environment (Pepple, 2020; Bekuru & Nwinyokpugi, 2021; Abdulkazeem, 2025; Opuwari, 2024; Bature & Ngozi, 2025) [1, 4, 5, 24, 25]. Therefore, this study investigated the relationship between artificial intelligence adoption and organisational transformation of bakery firms in Port Harcourt, Rivers State, Nigeria.

Conceptual Framework



Source: Researcher's Conceptualisation (2026)

Fig 1: Conceptual Framework Showing Relationship between Artificial Intelligence (AI) Adoption and Organisational Transformation.

Aim and Objectives

The aim of this study was to investigate the relationship between artificial intelligence adoption and organisational transformation of bakery firms in Port Harcourt, Rivers State. The specific objectives were to:

1. examine the relationship between predictive maintenance and knowledge transfer of bakery firms in Port Harcourt, Rivers State.
2. ascertain the relationship between predictive maintenance and innovation of bakery firms in Port Harcourt, Rivers State.
3. investigate the relationship between smart production scheduling and knowledge transfer of bakery firms in Port Harcourt, Rivers State.
4. examine the relationship between smart production scheduling and innovation of bakery firms in Port Harcourt, Rivers State.

Research Questions

1. What is the "relationship between predictive maintenance and knowledge transfer of bakery firms in Port Harcourt, Rivers State?
2. How does predictive maintenance relate with innovation of bakery firms in Port Harcourt, Rivers State?
3. What is the relationship between smart production scheduling and knowledge transfer of bakery firms in Port Harcourt, Rivers State?
4. How does smart production scheduling relate with innovation of bakery firms in Port Harcourt, Rivers State?

Research Hypotheses

The following null hypotheses were tested at a significance level of 0.01.

Ho_1: There is no significant relationship between predictive maintenance and knowledge transfer of bakery firms in Port Harcourt, Rivers State.

Ho_2: There is no significant relationship between predictive maintenance and innovation of bakery firms in Port Harcourt, Rivers State.

Ho_3: There is no significant relationship between smart production scheduling and knowledge transfer of bakery firms in Port Harcourt, Rivers State.

Ho_4: There is no significant relationship between smart production scheduling and innovation of bakery firms in Port Harcourt, Rivers State.

Review of Related Literature

Concept of Artificial Intelligence Adoption

From the manufacturing perspective, the concept of Artificial Intelligence (AI) adoption refers to the deliberate integration of data-driven algorithms, machine learning models, and intelligent systems into core production and managerial activities to improve efficiency, flexibility, and decision-making. In the context of Industry 4.0, AI is seen as a pivotal technology that reshapes production system design, planning, process control, quality assurance, maintenance, and automated assembly, enabling the transition from traditional factories to smart manufacturing environments (Gao *et al*., 2024; Elahi *et al*., 2023; Peres *et al*., 2018) [11, 12]. By analysing large volumes of real-time data from machines, sensors, and enterprise systems, AI supports optimized process modelling, continuous improvement, and rapid response to disturbances and changing customer needs (Gao *et al*., Elahi *et al*., 2023) [11]. Typical adoption areas include predictive maintenance, where AI forecasts equipment failures from sensor and historical data to reduce unplanned downtime and maintenance costs (Rakholia *et al*., 2024; Chatterjee *et al*., 2021; Prabu *et al*., 2025) [7, 27, 28], production and resource optimization, where reinforcement learning and advanced analytics balance throughput, energy use, and scheduling efficiency (Elahi *et al*., 2023; Jin *et al*., 2025) [11, 17], and quality control, where computer vision and pattern recognition detect defects early and support zero-defect manufacturing (Elahi *et al*., 2023; Peres *et al*., 2020) [11, 26].

Conceptually, AI adoption is not only a technological decision but also an organizational and strategic one: firm-level uptake depends strongly on digital skills, R&D intensity, company size, and readiness to invest in data infrastructure and change management (Jin *et al*., 2025; Zeba *et al*., 2021) [17, 32] Studies using technology-organization-environment and TAM-based models show that perceived usefulness, ease of use, leadership support, and socio-environmental pressures shape employees' and managers' intentions to embrace AI-based tools (Kinkel *et al*., 2022 Chatterjee *et al*., 2021) [7, 18]. At the same time, firms face foundational barriers, such as legacy equipment, data quality issues, high upfront costs, skills gaps, and concerns about transparency and trustworthiness of AI decisions. When these challenges are systematically addressed through resource orchestration, workforce reskilling, robust data platforms, and staged pilot projects AI adoption can drive digital transformation, enabling more autonomous, resilient, and innovative manufacturing operations that enhance competitiveness in dynamic markets (Rakholia *et al*., 2024; Chatterjee *et al*., 2021; Wan *et al*., 2023) [7, 28, 30]. However, this study made used of predictive maintenance and smart production scheduling as dimensions of artificial intelligence adoption.

Predictive Maintenance: Predictive maintenance uses data analytics and machine learning to anticipate equipment failures before they occur. It collects real-time data from sensors installed on machines such as motors, conveyors, and production lines. AI systems analyze patterns in vibration, temperature, and performance to detect early warning signs of faults. This enables firms to schedule timely maintenance activities and avoid unexpected breakdowns (Ola-Oluwa, 2024; Bekuru & Nwinyokpugi, 2021; Omonzejele & Okogun, 2025) [5, 22, 23]. As a result, production downtime is significantly reduced. Predictive maintenance also helps extend the lifespan of equipment by preventing severe damage. It improves operational efficiency by ensuring machines operate at optimal conditions. In addition, it reduces maintenance costs by minimizing emergency repairs. The approach supports better planning of spare parts and labor resources.

Smart Production Scheduling: Smart production scheduling refers to the use of AI algorithms to plan and coordinate manufacturing activities efficiently. It analyzes data on customer demand, machine availability, workforce capacity, and delivery deadlines to create optimal production schedules. This enables firms to allocate resources effectively and reduce production bottlenecks. Smart scheduling helps minimize idle time of machines and workers, thereby improving overall productivity. It also allows firms to adjust schedules in real time when disruptions such as machine breakdowns or urgent orders occur (Hassan, 2024; Gao *et al*., 2024) [12, 14]. By improving workflow coordination, it enhances timely order fulfillment. The system supports better inventory management by aligning production with demand patterns. In addition, it improves operational flexibility and responsiveness. Smart production scheduling reduces operational costs and waste.

Concept of Organisational Transformation

Organisational transformation refers to deep, planned changes in structures, processes, culture and capabilities that enable the organisation to compete effectively in a digital, data-driven environment. In contemporary manufacturing, this transformation is increasingly framed as digital transformation, where firms reconfigure operations, business models and organisational design around advanced digital technologies and data flows (Zhang & Wang, 2023; Moghrabi *et al*., 2023) [20, 30, 33]. Rather than a one-off project, it is an evolutionary process in which processes and capabilities are continually optimised, and core technology innovation, business model re-engineering and organisational structure optimisation reinforce one another to build sustainable competitive advantage (Zhang & Wang, 2023; Wu *et al*., 2024) [31, 33]. Internally, transformation reshapes production systems, decision-making and roles: leaner, flatter and more flexible structures, greater cross-functional integration, and new job profiles that combine technical and non-technical competencies are commonly observed as firms adopt Industry 4.0 technologies (Cimini *et al*., 2020; Imran *et al*., 2021) [9, 15].

At the cultural level, organisational transformation involves shifting toward a more digital organisational culture characterised by collaboration, openness to change, continuous learning and data-driven decision-making, which strongly conditions how successfully digital initiatives take root (Jewapatarakul & Ueasangkomsate, 2024) [16]. Leadership commitment, clear strategic intent and organisational readiness—covering vision, skills, resources and communication are repeatedly identified as critical conditions for initiating and sustaining transformation (Imran *et al*., 2021; Chirumalla *et al*., 2025; Ghafoori *et al*., 2024) [8, 13, 15]. Studies across manufacturing sectors show that when transformation is well aligned with strategy and supported by appropriate structures and culture, firms gain agility, customer-centricity, innovation capacity and operational efficiency. Conversely, pursuing technology adoption without parallel organisational change often produces fragmentation, resistance and under-utilisation of digital tools (Machado *et al*., 2021; Nour *et al*., 2025; Björkdahl, 2020) [6, 19, 21]. However, this study measured organizational transformation in terms of knowledge transfer and innovation.

Knowledge Transfer: Knowledge transfer involves the systematic sharing and dissemination of skills, information, and expertise across the organisation. It ensures that valuable technical know-how, best practices, and lessons learned from experienced employees are passed on to others, including new staff. Effective knowledge transfer fosters continuous learning and innovation by enabling employees to build on existing knowledge. It also improves problem-solving and decision-making by providing access to relevant information (Moghrabi *et al*., 2023; Chirumalla *et al*., 2025) [8, 20]. In production firms, this process enhances operational efficiency and quality by standardizing procedures. Knowledge transfer supports collaboration between departments, breaking down silos. It helps the organisation adapt quickly to technological changes and market demands. Digital tools and AI can facilitate this transfer by capturing and distributing knowledge.

Innovation: Innovation drives the development and implementation of new ideas, processes, products, and technologies. It enables firms to improve efficiency, reduce costs, and enhance product quality, helping them stay competitive in rapidly changing markets. Innovation encourages creative problem-solving and the adoption of advanced technologies such as automation and artificial intelligence (Ghafoori *et al*., 2024; Moghrabi *et al*., 2023; Imran *et al*., 2021) [13, 15, 20]. It fosters a culture of continuous improvement where employees are motivated to explore better ways of working. In production firms, innovation can lead to the introduction of new manufacturing methods, materials, or designs that increase productivity. It also supports responsiveness to customer needs and market trends (Chirumalla *et al*., 2025) [8]. By integrating innovation into their transformation strategies, firms can adapt to disruptions and seize new business opportunities.

Theoretical Review

The study used technology acceptance model as its theoretical anchor. The Technology Acceptance Model (TAM) was propounded by Fred Davis in 1989 to explain how users accept and adopt new technologies. The model assumes that an individual’s intention to use a technology is primarily determined by two key factors: perceived usefulness and perceived ease of use. Perceived usefulness refers to the degree to which a person believes that using a system will improve job performance (Bekuru & Nwinyokpugi, 2021; Aliu *et al*., 2025) [3, 5]. Perceived ease of use relates to the extent to which a person believes that using the system will be free from effort. TAM assumes that when users find a technology beneficial and easy to operate, they are more likely to accept and use it. It also suggests that external factors such as training and system design influence these perceptions. The model further assumes that user attitude mediates the relationship between beliefs and actual usage.

The Technology Acceptance Model (TAM) is essential to the study as it focuses on how employees and managers accept new technologies. TAM emphasizes perceived usefulness, which explains why bakery staff are more likely to adopt AI tools such as predictive maintenance and smart production scheduling when they believe these technologies improve productivity, reduce waste, and enhance product quality. It also highlights perceived ease of use, meaning that AI systems that are simple and user-friendly are more easily integrated into daily bakery operations. When bakery employees accept and use AI technologies, operational processes become more efficient and digitally driven. This acceptance leads to improved knowledge sharing, better coordination, and enhanced innovation practices. TAM also explains how training and management support influence positive attitudes toward AI adoption. As workers become comfortable with AI tools, resistance to change is reduced. Increased usage of AI systems encourages data-driven decision-making and workflow automation. Over time, these changes reshape organisational structures and work culture. TAM therefore provides a framework for understanding how human acceptance of AI enables successful organisational transformation. In bakery firms, this transformation results in improved efficiency, service delivery, and competitive advantage.

Methodology

The study adopted the correlational research design. The population of this study comprised of 20 selected registered bakery firms operating in Port Harcourt. The information was obtained from https://www.finelib.com/cities/port-harcourt/business/-food/-confectioneries. The entire bakery firms were adopted as the sample size for the study. The study adopted a census approach, the census approach enabled the researcher to study the entire population with a focus on managers. Five managers (business development manager, production manager, brand manager, sales area manager and marketing manager) were targeted in generating information for this study. In this case, the questionnaire was distributed in the frame of five (5) copies per bakery firm. A total of one hundred (100) respondents were used as the study subjects. The questionnaire was the primary source for data collection in the study which was designed in a likert response options. Pearson Product Moment Correlation (PPMC) was used to test the formulated hypotheses at 0.01 level of significance. 82 (82%) copies of the questionnaire was accurately filled and retrieved, which formed the date for analysis.

Results

Ho_1: There is no significant relationship between predictive maintenance and knowledge transfer of bakery firms in Port Harcourt, Rivers State.

Table 1: Correlation between Predictive Maintenance and Knowledge Transfer

			Predictive Maintenance	Knowledge Transfer
	Predictive Maintenance	Pearson Correlation	1	.817**
		Sig. (2-tailed)	.	.000
		N	82	82
	Knowledge Transfer	Pearson Correlation	.817**	1
		Sig. (2-tailed)	.000	.
		N	82	82

**. Correlation is significant at the 0.01 level (2-tailed)

Table 1 above shows r value of 0.817 at a significance level of 0.00 which is less than the chosen alpha level of 0.01. Since the significance value 0.000 is less than the alpha level of 0.01, the null hypothesis (Ho_1) which states that there is no significant relationship between predictive maintenance and knowledge transfer of bakery firms in Port Harcourt, Rivers State was rejected and the alternate hypothesis accepted. This implies that there is a very strong significant relationship between predictive maintenance and knowledge transfer bakery firms in Port Harcourt, Rivers State.

Ho_2: There is no significant relationship between predictive maintenance and innovation of bakery firms in Port Harcourt, Rivers State.

Table 2: Correlation between Predictive Maintenance and Innovation

			Predictive Maintenance	Innovation
	Predictive Maintenance	Pearson Correlation	1	.703**
		Sig. (2-tailed)	.	.000
		N	82	82
	Innovation	Pearson Correlation	.703**	1
		Sig. (2-tailed)	.000	.
		N	82	82

**. Correlation is significant at the 0.01 level (2-tailed)

Table 2 above shows r value of 0.703 at a significance level of 0.00 which is less than the chosen alpha level of 0.01. Since the significance value 0.000 is less than the alpha level of 0.01, the null hypothesis (Ho_2) which states that there is no significant relationship between predictive maintenance and innovation of bakery firms in Port Harcourt, Rivers State was rejected and the alternate hypothesis accepted. This implies that there is a strong significant relationship between predictive maintenance and innovation of bakery firms in Port Harcourt, Rivers State.

Ho_3: There is no significant relationship between smart production scheduling and knowledge transfer of bakery firms in Port Harcourt, Rivers State.

Table 3: Correlation between Smart Production Scheduling and Knowledge Transfer

		Smart Production Scheduling	Knowledge Transfer
Smart Production Scheduling	Pearson Correlation	1	.707**
	Sig. (2-tailed)	.	.000
	N	82	82
Knowledge Transfer	Pearson Correlation	.707**	1
	Sig. (2-tailed)	.000	.
	N	82	82

**. Correlation is significant at the 0.01 level (2-tailed)

Table 3 above shows r value of 0.707 at a significance level of 0.00 which is less than the chosen alpha level of 0.01. Since the significance value 0.000 is less than the alpha level of 0.01, the null hypothesis (Ho_3) which states that there is no significant relationship between smart production scheduling and knowledge transfer of bakery firms in Port Harcourt, Rivers State was rejected and the alternate hypothesis accepted. This implies that there is a strong significant relationship between smart production scheduling and knowledge transfer of bakery firms in Port Harcourt, Rivers State.

Ho_4: There is no significant relationship between smart production scheduling and innovation of bakery firms in Port Harcourt, Rivers State.

Table 4: Correlation between Smart Production Scheduling and Innovation

		Smart Production Scheduling	Innovation
Smart Production Scheduling	Pearson Correlation	1	.672**
	Sig. (2-tailed)	.	.000
	N	82	82
Innovation	Pearson Correlation	.672**	1
	Sig. (2-tailed)	.000	.
	N	82	82

**. Correlation is significant at the 0.01 level (2-tailed)

Table 4 above shows r value of 0.672 at a significance level of 0.00 which is less than the chosen alpha level of 0.01. Since the significance value 0.000 is less than the alpha level of 0.01, the null hypothesis (Ho_4) which states that there is no significant relationship between smart production scheduling and innovation of bakery firms in Port Harcourt, Rivers State was rejected and the alternate hypothesis accepted. This implies that there is a strong significant relationship between smart production scheduling and innovation of bakery firms in Port Harcourt, Rivers State.

Discussion of Findings

The findings of this study revealed significant positive relationships between artificial intelligence adoption and organisational transformation of bakery firms in Port Harcourt, Rivers State. These findings are in line with the view of Chatterjee *et al*. (2021) [7] and Jin (2025) [17] which stated that manufacturing performance are enhanced through AI and machine learning: applications in predictive maintenance and production optimization. Drawing from the above, predictive maintenance enables bakeries to collect real-time data from ovens, mixers, and packaging machines, which helps employees understand equipment performance patterns. This data is stored and shared across departments, allowing technicians and production staff to learn from past faults and maintenance practices. As a result, technical knowledge is transferred more efficiently among workers and across shifts. Smart production scheduling also supports knowledge transfer by integrating information from sales, production, and inventory units into a single digital system (Ghafoori *et al*., 2024; Aliu *et al*., 2025) [3, 13]. This improves communication, coordination, and transparency in bakery operations. Employees gain better insight into workflow processes and demand trends, which strengthens organisational learning.

Furthermore, predictive maintenance reduces machine downtime, creating opportunities for staff to experiment with new production methods and recipes. Smart scheduling allows bakeries to test new product lines and adjust production plans based on customer demand. These practices encourage creative problem-solving and process improvements. AI-driven insights also support data-based decision-making, which stimulates innovative thinking (Edison, 2024; Bekuru & Nwinyokpugi, 2021; Stornelli *et al*., 2024) [5, 29]. Over time, continuous learning and experimentation lead to the development of new baking techniques and improved service delivery. The combined use of AI tools helps bakeries become more flexible and adaptive to market changes. It also promotes a culture of continuous improvement and technological advancement.

Conclusion

Artificial intelligence adoption transforms traditional bakery operations into knowledge-driven and innovative production systems. This transformation strengthens competitiveness and long-term sustainability of bakery firms.

Recommendations

1. Bakery firms should link AI maintenance systems to digital knowledge platforms where equipment data, fault reports, and repair solutions are stored and shared. This will enable technicians and production staff to access past experiences, learn best practices and transfer technical knowledge more effectively, thereby supporting organisational learning.
2. Management should incorporate training programs that would teach employees how to interpret AI-generated maintenance insights, as such would improve staff competence, encourage creative problem-solving, and promote innovative practices.

3. Bakery firms should integrate data from sales, inventory, and production units into a unified AI platform to promote effective information sharing and collaboration among employees, thereby enhancing knowledge transfer in bakery operations.
4. Management should utilize AI systems to adjust schedules in real time based on demand changes and production disruptions, as such would encourage flexible work practices, support experimentation with new production methods, and foster continuous innovation within the organisation.

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