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# Leveraging Digital Transformation for Responsible Food Production and Distribution in an Emerging Economy's Manufacturing Sector

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**Abstract**

**Purpose:** This study explores the role of digital transformation in enhancing responsible food production and distribution within Nigerian manufacturing firms, focusing on supply chain digitization and predictive maintenance. While digital technologies hold significant potential to reduce waste, improve energy efficiency, and optimize distribution, adoption barriers in Nigeria have contributed to persistent food waste, high energy consumption, and inefficiencies in logistics and distribution systems. **Research design, data, and methodology:** Based on the resource-based view theoretical foundation, the study adopts a survey research design. Primary data were collected through a closed-ended structured questionnaire. This was administered to 274 production engineers and warehouse managers and food items distributors, IT professionals and supply chain managers in the Nigerian food manufacturing sector. The Partial Least Squares – Structural Equation Modelling (PLS-SEM) was employed to analyse the data using SmartPLS software. **Results:** The results demonstrate that supply chain digitization and predictive maintenance significantly enhance responsible food production and distribution by reducing waste and improving logistics resource efficiency. **Conclusions:** The study underscores the critical role of digital transformation tools in achieving sustainability in food production and distribution. The implication is by integrating digitalisation into food supply chain processes and functions, manufacturing industry can realize their responsible production goals.

**Keywords:** Digital Transformation, Responsible Production, Responsible Product Distribution, Supply Chain Digitalization, Predictive Maintenance.

**JEL Classification Code:** E44, F31, F37, G15

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# 1. Introduction

Over the years, organizations have reconfigured their production and distribution processes to suite consumers changing needs and tastes, and in the process, caused significant environmental and societal damage. These processes have led to unsustainable economic, social, and environmental challenges, impacting both consumers and the environment (Hanenkamp & Zipse, 2023). The necessity for responsible production and distribution practices is critical due to the heightened effects of climate change, resource depletion, and ecological degradation. To eliminate unsustainable production and distribution, businesses must minimize waste, and reduce energy depletion, and inefficient use of material resources. Products must be designed, produced, distributed, disposed of, or recycled in ways that ensure environmental safety and efficient resource usage (Ufua et al., 2021). This concept of responsible production aligns with the United Nations' Sustainable Development Goals (SDGs), particularly SDG-12 (Garetti & Taisch, 2012).

Responsible production entails improving production processes and systems to reduce energy and water consumption, implementing waste management strategies to recycle or repurpose byproducts, and minimizing harmful emissions (Adekunle & Dakare, 2020). The policy concern necessitates the commodity to provide healthy and safe working conditions, maintain employees' rights and contribute positively to the communities in which they operate. By prioritizing sustainability, manufacturing companies can reduce costs, comply with environmental regulations, enhance their brand reputation, and meet the growing demand from consumers and stakeholders for environmentally responsible products (Nwagu & Ogbo, 2023). Sustainable production is not only beneficial for the environment but also creates a competitive advantage by driving innovation and operational efficiencies (Richard et al., 2022).

In response, manufacturing organizations are increasingly integrating digital transformation as a strategic approach to responsible production (Ghobakhloo, 2020). Digital technologies can be held as one of the derivative outcomes of industry 4. 0 getting through large volumes of data has turned manufacturing into Smart Manufacturing Systems (SMS) through the use of technologies like the Internet of Things (IoT), Cyber Physical Systems (CPS), and Artificial Intelligence (AI), (Lottuet et al., 2023; Ikenwe & Udem, 2022). This transformation significantly impacts the achievement of manufacturing objectives, aiming to enhance intelligence, and efficiency in operations (Quintás et al., 2018; Dingler & Enkel, 2016).

Today, digital tools such as AI analytics, machine learning algorithms, IoT sensors, and digital twins are widely used to enhance machine efficiency, predict maintenance schedules to reduce unplanned downtime, monitor production processes for quality control, and optimize production schedules and workflows (Mohapatra et al., 2022). These advancements have led to lower operating costs, improved efficiency, and overall better bottom-line performance. However, despite these benefits, there is limited empirical evidence on how digital transformation contributes to responsible production and distribution in the food manufacturing sector. The implication is that Nigerian food manufacturing firms face significant challenges in harnessing digital technologies for responsible production and distribution, leading to food wastage, high energy consumption, and supply chain inefficiencies. Therefore, this study explores how the adoption of digital transformation can drive responsible production and distribution in Nigeria's food manufacturing sector.

# 2. Literature Review and Hypothesis Development

## 2.1. Digital Transformation

Digital transformations (DT) have shifted from being an opportunity to a necessity which meets the demands of an increasing global population (Bouncken et al., 2021). This has resulted in the alteration of various organizational structures and processes since it addresses efficiency and effectiveness issues (Heavin and Power, 2018). Digital technologies are recognized as pivotal assets in organisational transformation due to their disruptive nature and broad-ranging effects (Besson & Rowe, 2012). Changes at multiple organizational levels are necessary for successful DT initiatives. These changes include reconfiguring processes, repurposing resources, cultivating a digital culture, and adapting core business (Allam & Dhunny, 2019; Resca et al., 2013; Singh & Hess, 2022). According to Chiemeke and Imafidor (2020) digital transformation in manufacturing sector is known as the use and integration of modern digital technology to simplify and enhance production processes. This concept emphasizes the importance of digital technologies and systems in work automation, waste reduction, and food product accuracy and uniformity (Adeoye, 2020; Danquah, & Owusu, 2021). For example, the integration of IoT (Internet of Things) devices and sensors in food processing facilities allows for real-time monitoring of equipment and ambient conditions, ensuring that production parameters remain within acceptable limits. This technology integration improves productivity and reduces downtime by identifying and addressing possible issues before they become major problems (Ufua, et al., 2021; Buba et al., 2022).

## 2.2. Responsible Production and Distribution

Responsible production involves converting raw materials into valuable goods while carefully considering social and environmental impacts. As sustainability concerns have grown, stakeholders across government, NGOs, corporations, and academia now widely acknowledge the unsustainable nature of traditional development models (Mohapatra et al., 2022; John et al., 2024). For instance, Olokundun et al. (2021) analyzed the detrimental effects of unchecked natural resource use, industrialization, pollution, and population growth, all of which exacerbate resource shortages globally. Addressing this, Despeisse et al. (2012) note that increasing scarcity and higher costs of materials and energy are driving manufacturers to adopt more environmentally responsible practices.

Responsible distribution complements these efforts by ensuring that goods are transported, stored, and delivered in ways that minimize environmental impact and uphold social responsibility (Okogwu et al., 2023). This approach emphasizes reducing emissions, optimizing logistics processes, and using packaging that minimizes waste, reflecting a commitment to sustainable development. For companies, embracing responsible distribution aligns with lean manufacturing principles that aim to reduce waste and enhance resource efficiency (Ufua et al., 2020). This combination of responsible production and distribution is driven by factors like stakeholder demand for transparency, regulatory pressures, and economic incentives, such as cost savings and wider acceptance of products in the market (Ogbari et al., 2017; Trianni et al., 2019).

Together, responsible production and distribution address the interconnected challenges of resource depletion, waste management, and community well-being, reinforcing manufacturing's role in sustainable socio-economic development (Moldavska & Welo, 2017). By adopting these practices, companies not only improve operational efficiency but also contribute to a sustainable future.

## 2.3. Predictive Maintenance

Predictive maintenance emerges as a cornerstone of Industry 4.0, leveraging historical data, models, and domain knowledge to anticipate equipment failures and trends (Sezer et al., 2018). This evolution underscores the critical importance of maintenance in modern industries, driven by the increasing complexity of interactions contained in lengthy manufacturing networks (Sezer et al., 2018). Complementing predictive maintenance is also known as the Industrial Internet of Things (IoT), which utilizes IoT technologies within industrial settings to enhance efficiency and enable data-driven decision-making (Sezer et al., 2018). The focus on "smart machines" draws attention to the possibility that they may manage data more accurately and consistently than people (Sezer et al., 2018). The utilization of data from multiple sensors offers opportunities for predicting the remaining lifespan of assets in Industry 4.0 environments (Yan et al., 2018), presenting novel opportunities for proactive maintenance actions to avoid downtime and optimize maintenance activities (Wu et al., 2016). Predictive maintenance practices fall under four main types: corrective, preventive, predictive, and prescriptive (Nemeth et al., 2018). Corrective maintenance addresses faults or signs of failure as they occur, while preventive maintenance relies on scheduled interventions at a specific time. Predictive maintenance on the other hand, makes use of time-based data and expertise to foresee probable problems and prevent unscheduled downtime. Prescriptive maintenance focuses on determining the actions necessary to control the occurrence of specific events, offering valuable guidance for optimizing maintenance processes and decision-making (Nemeth et al., 2018).

## 2.4. Sustainable Waste Reduction

The increase in the world's population and the development of new technology have made it worse to exhaust resources hence causing rise in environmental pollution and deplete of the available natural resources (Govindan & Hasanagic, 2018; Garza-Reyes et al., 2019). Due to this increasing consumption of resources, there is a need to have proper management policies, and proper management strategies (Zhang et al., 2019; Carmeli et al., 2020). In response to this seemingly promising key, the CE has surfaced and put out an alternative that extends beyond the traditional "take-make-dispose" linear model and toward practices that center on resource restoring recycling, and reuse (Govindan & Hasanagic, 2018; Scarpellini et al., 2020). CE principles build around the key concepts such as waste minimization the maximization of usage, and utilization of resources that are scarce or limited, which are in tune with the SDG 12 on responsible consumption as well as production (Nadeem et al., 2017; Ogbari et al., 2024). Strategies such as waste reduction, reuse, repair, and recycling, inherent in circular approaches, offer a host of environmental, economic, and social benefits while positively contributing to related SDGs like SDG 6, SDG 7, and SDG 15 (Schroeder et al., 2019). However, the uptake of circular economy strategies in manufacturing remains limited, attributed to factors such as the concept's early stage, a lack of innovation tools oriented towards CE, and underestimation of the role of digital technologies (Sousa-Zomer et al., 2018; Brown et al., 2019).

The effective application of digital technologies leading to better resource management and decision-making, where IoT and big data are also used, becomes crucial to enabling CE (Lacy et al., 2020). For example, IoT facilitates the monitoring of natural capital and big data helps in enhancing the industrial symbiosis's matching of waste to resource (Antikainen et al., 2018; Low et al., 2018). Lean manufacturing, following the Toyota Production Structure, minimizes waste, eradicating activities that add no value following the idea of continuous improvement (Majewski, 2019; Alfarisi & Sutopo, 2019; Prasad et al., 2019). Lean principles identify and eliminate seven types of waste, optimizing resource use and minimizing waste (Lin et al., 2020). Integrating circular and lean principles offers a comprehensive approach to waste reduction, contributing to sustainable production and consumption and SDG 12.

## 2.5. Supply Chain Digitization and Sustainable Waste Reduction

In today's dynamic world, supply chains must be managed and their performance must be elevated via effective use of strategic digital resources. This supports the Resource-Based View (RBV) theory on which our study is based. According to the RBV theory, the competitive advantage of a firm can be enhanced by the acquisition of resources that are rare, valuable and hard to imitate by the competitors, and have no substitutes (Rivard et al., 2006; Uyanik, 2023). These resources enable firms to withstand environmental challenges and seize emerging opportunities. We argue throughout this paper that digital technologies, such supply chain digitization, and as predictive maintenance should be adopted by food manufacturing firms as strategic resources. These technologies can optimize food production processes, reduce waste, and enhance sustainability. By integrating these digital advancements into their supply chain and equipment maintenance, food companies can improve operational efficiency, minimize the use of critical resources, and reduce waste, thereby advancing towards sustainable production.

Supply chain digitization entails leveraging digital technologies to synchronize production schedules, improve inventory management, and optimize logistics operations (Adeyemi, et al., 2024; Ogah, & Onuoha, 2022). In a recent food sector research, Ajayi and Laseinde (2023) emphasize that product freshness and safety are paramount, hence, digitization plays a critical role in ensuring real-time monitoring and control to reduce waste. Khalifa et al. (2021) opined that by implementing IoT sensors and blockchain technology, for instance, manufacturers can trace the origin of raw materials, monitor storage conditions, and also monitor the process of goods done through the supply chain, thereby enhancing food safety and reducing waste in the production process. Studies such Rahamneh et al. (2023) and Olaghere, et al. (2023) have also highlighted that supply chain digitalization capability is particularly beneficial in situation where demand can be highly variable and production needs to be both flexible and responsive (Shettima & Sharma, 2020). Given these benefits, it is expected that digital supply chain would be a significant tool to ensure waste reduction from the perspective of food manufacturing. Therefore, we postulate that:

**H1:** Supply chain digitization is significantly related to sustainable waste reduction.

## 2.6. Predictive Maintenance and Sustainable Waste Reduction

Predictive maintenance emerges as a core achievement of Industry 4.0, leveraging historical data, models, and domain knowledge to anticipate equipment failures and trends (Sezer et al., 2018). This evolution underscores the critical importance of maintenance in modern industries, driven by the increasing complexity of interactions within extended manufacturing ecosystems (Sezer et al., 2018). The utilization of data from multiple sensors offers opportunities for predicting the remaining lifespan of assets (Hess et al., 2016). Proactive maintenance actions helps to avoid downtime and optimize maintenance activities (Wu et al., 2016). Predictive maintenance leverages advancements in sensor technology and machine learning algorithms to dynamically monitor and predict system states, enabling proactive measures to prevent critical failures and accidents (Omri et al., 2021). According to Mohapatra et al. (2022), adopting predictive maintenance technologies facilitates maintenance planning and enhancing operational efficiency.

John et al. (2024) and Javaid et al. (2021) emphasize predictive maintenance ability to optimize maintenance schedules, leading to fewer equipment failures and breakdowns, which directly minimizes waste generation. By anticipating and addressing potential issues before they escalate, Etukudoh (2024) notes that predictive maintenance reduces the need for unplanned repairs and replacements, thus conserving resources and decreasing waste associated with discarded parts and equipment (Chakroun et al., 2024). In addition, a country-wide study of manufacturing industries in Oman by Cakir et al. (2021) reported that data-driven predictive maintenance enable proactive identification of quality failure in the production process, further contributing to waste reduction efforts. Similarly, Poór et al. (2019) found that predictive maintenance is related to equipment longevity, reliability, and cost-effectiveness. Given, the existing knowledge in the literature, and in line with our theoretical foundation, we expect predictive maintenance to significantly influence manufacturing operations' ability to implement waste reduction in their quest for achieving sustainable production. Hence, we propose that:

**H2:** Predictive maintenance is significantly related to sustainable waste reduction

## 3. Methodology

### 3.1. Research Design and Sample

The study's adoption of a cross-sectional research design was driven by its use of a quantitative research technique. This design allows for the collection of primary data through the structured questionnaire from relevant departments in food manufacturing companies in Nigeria. The study employed the random sampling approach, and the target population, generally, were experienced professionals and managers in the production, information technology, logistics and supply chain units of all registered processed food manufacturing companies in Nigeria. Some of the data which include contact details of the registered companies were obtained from the Manufacturers Association of Nigeria and used for the purpose of this study. A total number of samples reached with copies of the questionnaire were 658 of which 274 valid responses were received and used for estimation purpose. This represents a response rate of 41.64%, considered adequate for research in the manufacturing sector when compared to contemporary sustainability and digital technology studies in emerging economies (Kaynak & Hartley, 2008; Scholten & Fynes, 2017) (Mugenda & Mugenda, 2003).

### 3.2. Data Collection and Variable Measurement

The quantitative data sourcing technique that was used in the study was the close ended structured questionnaire. The questionnaire method was chosen because of its advantages such as standardization, coverage, economy, and the need to collect cross sectional information at one time. Moreover, its wide usage for collecting data for sustainability study in manufacturing propels its adoption in this study. The questionnaire was administered based on a 5 Likert scale structure which has the maximum mark as 5 while the minimum one was 1. After each item, respondents were to provide a 5 point Likert type response that included strongly agree (5 points) and strongly disagree (1). There were a total of 25 questions developed within the context of the study variables and, in addition, to the general aim of the study.

The variables of this study include; digital transformation as the independent variable and sustainable production as the dependent variable. Digital transformation was further decomposed into two measures, namely supply chain digitization, and predictive maintenance. Sustainable production has waste reduction as its indicator. Questionnaire items that measured each variable were adapted from past studies with well-established validity. For instance, items related to supply chain digitization, and predictive maintenance were taken from (Adeyemi, et al., 2024; Ogah, & Onuoha, 2022; Khalifa, et al., 2021; Chakroun et al., 2024; Poór et al., 2019). While those measuring sustainable waste reduction was adapted from (Antikainen et al., 2018; Low et al., 2018). Some items were adopted to match the context of the study as advised by the two academic experts and one manufacturing industry professional that validated the research instrument. The diagrammatical representation of our theoretical model is as shown in Figure 1.

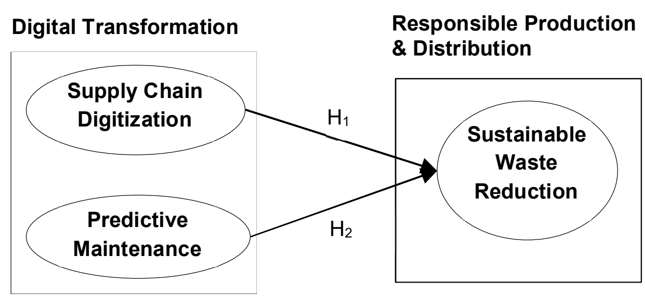


**Figure 1:** Theoretical Framework

Table 2 also provides sample of the questionnaire items that was used for data collection and analysis. Being a cross-sectional survey study, respondents were approached once by the lead investigator in company of two Field Assistants, they were trained on the procedures for data collection. To improve the reliability of the data collection instrument, pilot study was carried out with 30 respondents. The results were then used to determine the Cronbach alpha coefficient which measured the reliability of the questionnaire as shown in Table 2.

### 3.3. Estimation Techniques

To estimate the model, data was analysed using both descriptive (mean, standard deviation, frequency count, and percentages) and inferential (Structural equation modeling (SEM) statistical analysis. In that case, the Partial least square (SmartPLS) version of SEM was used for data processing. The SEM was used in estimating the model of the study, consisting of measurement and structural model. While the measurement model estimated model fitness, the structural model estimated relationship between variables by testing the research hypothesis.

Following a related study (Adekunle & Dakae, 2020) SEM was adopted as a key data analysis technique in this study because of its robustness, given its ability to estimate multiple variables at the same time, instead of just focusing on individual constructs that make up the model under study. According to, Collier, (2020) this gives more reliable results that can be better generalised than those from other regression model. Thus, in this study, the relationship between the two dimensions of digital transformation (Supply chain digitisation, and predictive maintenance) and sustainable performance measured by sustainable waste reduction was estimated as shown in Table 3.

# 4. Empirical Results

## 4.1. Descriptive Analysis of respondents' demographics

The details of the demographic characteristics of sample are summarized in Table 1. From the respondent's demographics, majority 169 (0.62%) were male respondents, and mostly managers 81(0.30%) from the production department, and majority 143(0.52%) having put in at least 5 years of work experience.

**Table 1:** Respondent's Demographic Data (N=274)

| Variables | Constructs | Frequency | Percent |
|---|---|---|---|
| Gender | Male | 169 | 0.62 |
| | Female | 105 | 0.38 |
| Age | 20-30 years | 203 | 0.74 |
| | 31 - 40 years | 52 | 0.19 |
| | 41- 50 years | 11 | 0.04 |
| | 51 years and above | 8 | 0.03 |
| Highest educational qualification | Diploma | 33 | 0.12 |
| | Bachelor | 141 | 0.51 |
| | Masters | 93 | 0.34 |
| | Doctorate | 7 | 0.03 |
| Working experience | Less than 5 years | 15 | 0.06 |
| | 5 – 10 years | 143 | 0.52 |
| | 11 – 15 years | 97 | 0.35 |
| | 16 years and above | 19 | 0.07 |
| Functional Units | IT | 76 | 0.28 |
| | Marketing | 23 | 0.08 |
| | Production | 81 | 0.30 |
| | Warehousing | 54 | 0.20 |
| | Logistics & Supply | 40 | 0.14 |

## 4.2. Model Estimation

In this section, we estimate the results of our model. The starting point is the estimation of measurement model for all the variables of the study (Supply chain digitization, predictive maintenance, and sustainable waste reduction). This is followed by the structured equation model estimation which enables the assessment of the relationship between the independent variables on the dependent variable

## 4.3. Measurement Model

The indices used in this study to assess the measurement model were confirmatory factor analysis (CFA), composite reliability (CR), Coefficient alpha, and

Average variance extracted (AVE). Results presented in Table 2 and Figure 2 demonstrate the model's fitness for supply chain digitization, predictive maintenance, and sustainable waste reduction. All constructs subjected to CFA yielded results that exceeded the minimum acceptable score of 0.5, as per Fornell and Larcker (2016). The CR scores of 0.88, 0.94 and 0.89 for supply chain digitization (SCD), predictive maintenance (PM), and sustainable waste reduction (SWR) respectively surpassed the acceptable benchmark of 0.70, consistent with Nunnally (2019). Additionally, the AVE values of 0.64, 0.79, and 0.68, which assess convergent validity, were above the 0.5 threshold stipulated by Fornell and Larcker (1981). Finally, the Cronbach's alpha test, a measure of model reliability, yielded values between: SCD=0.81, PM=0.91, and SWR=0.83, aligning with Hair et al. (2010). These results confirm the model's suitability for further analysis and estimation.

## 4.4. Structural Model Estimation

Following the testing of hypotheses, estimated result on the model is provided in Figure 2 and Table 3. It provides the path coefficients, t-statistics, and, most importantly, the p-value of significance. On the basis of these parameters, the results showed that the relationship between SCD and SWR construct (β: At 0. 169 and t-value: 2. 784 the coefficient is proven to be positive and statistically significant. Similarly, the results showed that PMI is positively and significantly related to SWR construct (β: 0. Here are the results of the test; p-value: 0. 392 and t-value: 2. 835). Therefore, based on the factual context of the model established above, all propositions posited for (H1 & H2) hold true. In addition, PMI having produced higher statistical coefficient (β: 0.554 and t-value: 8.325), has the higher predictive effect on SWR than SCD.

**Table 2**: Descriptive Score and Model Measurement for all Variables

| Variable | Construct | Mean | SD | Factor loading |
|---|---|---|---|---|
| Supply Chain Digitization **(AVE=0.64, Cronbach α = 0.81, CR=0.88)** | | | | |
| SCD1 | We use RFID scanners for real time stock tracking. | 2.79 | 1.30 | 0.84 |
| SCD2 | We use barcode to reduce product identification errors in our supply chain | 2.93 | 1.34 | 0.80 |
| SCD3 | We use GIS technology to speed up our product delivery process. | 2.95 | 1.34 | 0.83 |
| SCD4 | We deploy intelligent sensors to provide real-time alerts against transit issues in our supply chain | 3.27 | 1.27 | 0.88 |
| Predictive Maintenance **(AVE=0.79, Cronbach α = 0.91, CR=0.94)** | | | | |
| PM1 | We use pressure sensors in our production line to reduce number of equipment breakdowns. | 3.39 | 1.17 | 0.85 |
| PM2 | We use virtual replicas to predict equipment failure | 3.42 | 1.19 | 0.89 |
| PM3 | We use smart maintenance equipment to improve the accuracy of maintenance data | 3.52 | 1.29 | 0.92 |
| PM4 | We adopt multiple sensors, offering us the opportunity to predict equipment or asset lifespan | 3.54 | 1.21 | 0.88 |
| Sustainable Waste Reduction **(AVE= 0.68, Cronbach α = 0.83, CR=0.89)** | | | | |
| WR1 | The amount of raw materials wasted during production processes has significantly reduced | 3.92 | 1.21 | 0.86 |
| WR2 | Energy consumption has decreased through the use of digital technologies | 3.85 | 1.17 | 0.89 |
| WR3 | Defective products requiring rework or reject has reduced | 3.83 | 1.18 | 0.86 |
| WR4 | Production processes have been streamlined to eliminate unnecessary steps | 3.89 | 1.34 | 0.84 |

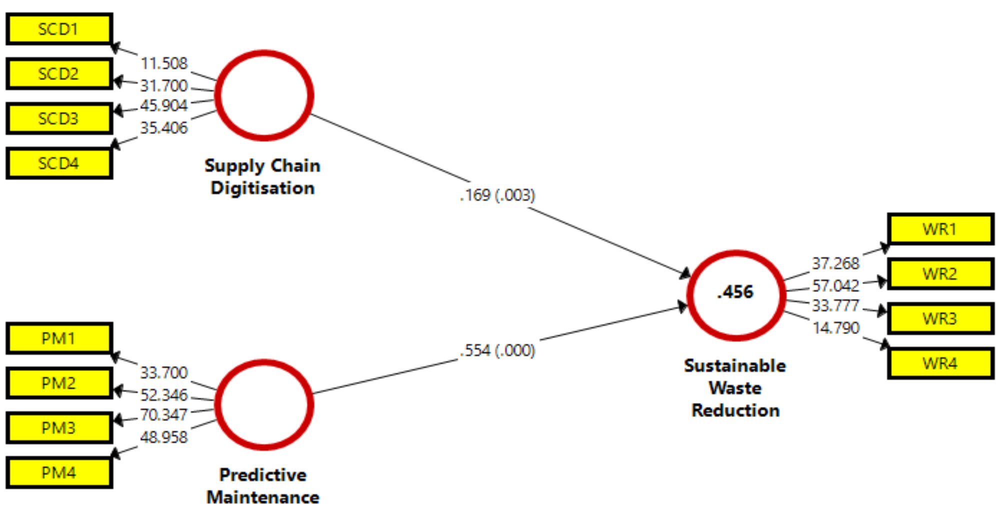


**Figure 2:** Empirical Path Diagram

**Table 3:** Structural Equation Model Results

| Paths | Path Estimate(β) | T Statistics | P Values | Decision |
|---|---|---|---|---|
| **H1:** Supply Chain Digitisation -> Sustainable Waste Reduction | 0.169 | 2.784 | 0.003 | Supported |
| **H2:** Predictive Maintenance -> Sustainable Waste Reduction | 0.554 | 8.325 | 0.000 | Supported |
| **Model fitness:** NFI=0.842, SRMR= 0.085, Chi-Square ($\chi^2$) = 340.150, D_ULS= 0.558, D_G= 0.209, RMSEA= 0.078_ | | | | |

The total goodness of model fit was assessed by adopting statistics including NFI(0.842), SRMR (0.085), D_ULS(0.558), D_G(0.209), and RMSEA(0.078). These results showed that all parameters were within the stipulated thresholds for goodness of model fit in line with Henseler and Sarstedt (2013), and Wetzels et al. (2009).

## 5. Discussion and Implications

Adopting digital transformation as a strategy for implementing sustainable production has proven to have significant potentials for food manufacturing organisations. The findings indicate that digitalizing food supply chain operations, and adopting predictive maintenance technologies can signify an important route to sustainable production by reducing waste in the production processes. Specifically, our study can report that the use of supply chain technologies such as RFID, barcode scanners, geographic information system (GIS), and intelligent sensors, positively impacts food production waste reduction. This can help practitioners in streamlining food supply chain processes, reducing errors related to product identification and minimizing systemic waste. Our findings is consistent with prior literature such as Ogah and Onuoha, (2022), Low et al. (2018) which reported that the incorporation and use of digital technologies in supply chain management can help in monitoring on-transit product quality, and improve product delivery times, thereby reducing the rate of product spoilage. Thus, we emphasize that integrating digitalization initiatives into food supply chain is crucial not only to reduce production waste, but by extension, to provide solution to food perishability and food insecurity issues in many emerging African economies.

Moreover, statistical evidence from the current study reveals that the influence PM on waste reduction was more compelling compared to SCD. Thus, integrating PM technologies such as virtual replicas, pressure sensors, and smart maintenance routines in the food manufacturing processes and system can provide a more enduring waste reduction benefits (Olokundun et al., 2022). In line with extant studies like Olokundun et al. (2022), and Adeyemi, et al. (2024), the benefits can include anticipating and preventing manufacturing equipment failure, ensuring continuous flow of production, minimizing machine downtime, and preventing shop floor injuries. For practitioners in the food manufacturing industry, it goes further that food production firms that prioritize PM are most likely than others to achieve reduced energy consumption, minimized material waste, and fewer defective products. In light of the findings, we further argue that unplanned equipment failures can generate significant food waste. Therefore, proactively identifying potential failure and disruption risks is crucial to ensuring that the production process remains efficient and material resources are optimally utilized.

Several theoretical implications emanate from this study. For instance, the growing literature in sustainable production receives a boost through the validation of empirical relationship existing between both supply chain digitization, predictive maintenance and sustainable waste reduction. This plays a crucial role as theoretical literature that acknowledges digital technologies as competitive resources and assets such as The RBV is further validated and strengthens. In addition, our study found predictive maintenance as a stronger technological innovation that can impact positively on sustainable production construct. This can be a potential for shaping future theoretical models that would prioritize PM as a crucial element of digital transformation, particularly in resource-intensive sectors like food manufacturing. Finally, the study contributes by identifying tangible and measurable metrics such as level of energy consumption, extent of material waste reduction in the sustainable food production processes. These metrics aligns with digital transformation, providing valuable inputs for future studies in sustainable manufacturing.

## 6. Conclusion and Future Research

The notion of responsible production and consumption is currently gaining impetus as firms continuously seek ways to achieve sustainable development goals 12. To that extent, strategies and initiatives that would simplify its actualization are welcome. This study was able investigates the relevance of digital transformation in driving sustainability in the food manufacturing sector. Overall, this study has found significant association between two digital transformation strategy- supply chain digitization, and predictive maintenance. In specific terms, we can make three conclusions in this study.

First, integrating digitalization into supply chain processes and function can revolutionize the production sustainability goals in food manufacturing. Second, a conscious effort to prioritize investment in predictive maintenance can help food manufacturing firms achieve sustainable waste reduction throughout the production processes and system. Third, food production firms that embrace digital supply chain and predictive maintenance protocols are most likely to reap the benefits of sustainability such as experiencing significant reduction in the amount of raw materials wasted during production processes; decreased level of energy consumption throughout all phases of production; reduced amount of defective products that are subjected to rework process or totally rejected; and a streamlined production processes that eliminates unnecessary steps in the workflow. To this extent, ppractitioners are encouraged to expand investment in digital solutions for real-time tracking and process optimization to reduce material waste and energy consumption thereby aligning with broader shifts towards sustainable production.

Similarly, three suggestions are provided that could shape the direction of future research in digital transformation and sustainable production. First, our interest had focused on the food manufacturing industry, an exploration of other related sector such as agriculture, packaging, and food retail distribution could provide fertile grounds for testing the influence of supply chain digitization and predictive maintenance on sustainable waste reduction. However, a cross-industry comparison could reveal sector-specific variations in the impact of digital transformation on sustainability. Second, we concentrated in just two forms or dimensions of digital transformation- SCD and PM. We are aware of the existence of others such as robotic automation, artificial intelligence, blockchain amongst others. Broadening the scope of future study to include some of these digital innovations could offer a more insights on how digitisation can contribute to sustainable manufacturing. Third, it is acknowledged in the literature (Lekan et al., 2023; Hansmann et al., 2012; Nsikan et al., 2023) that sustainability is anchored on three main pillars, namely- environmental, social, and economic sustainability. We would expect future research to extend investigation into other sustainability pillars such as social and economic sustainability; probably utilizing longitudinal methodology to understand the long term trend and holistic view of the impact of digital transformation on sustainable production.

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