Nutrient Composition and Sensory Properties of Cake Fortified with Watermelon (*Citrullus lanatus*) Rind Flour

Ukala, C.U.[1], Ogbu, H.C.[2], Nnaji J. O.[3], *Eya, D.N.[4], & Eze, C.F.[1]
[1]Department of Home Science and Management, University of Nigeria, Nsukka
[2]Department of Biochemistry, Ahmadu Bello University, Zaria, Kaduna State
[3]Department of Nutrition and Dietetics, University of Nigeria, Nsukka
*Correspondence email: chiforfavour87@gmail.com
https://orcid.org/0000-0001-9235-7290
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Abstract

The study determined the nutrient composition and sensory properties of cakes fortified with watermelon (*Citrullus lanatus*) rind flour. A quasi-experimental research design guided by four specific objectives was adopted. Cake samples were produced using wheat flour and watermelon rind flour blends formulated as K0 (100:0), K1 (80:20), K2 (70:30), and K3 (60:40). Sensory evaluation of the product was conducted first using a nine-point hedonic scale with 30 panelists to determine the most acceptable blend for subsequent nutritional evaluation. The most acceptable composite flour blend was analysed alongside the control sample for the nutrient content, including proximate, vitamin (provitamin A, B6, and C), and mineral (iron, zinc, and calcium) contents using standard methods. Data were analysed using mean, standard deviation, and paired-samples t-test in IBM SPSS version 23.0 at a significance level of $p < 0.05$. Results showed that for the proximate analysis, protein content increased from 4.925% in the control sample (K0; cake made with 100% wheat flour) to 5.280% in the fortified sample (K2; sample with 70:30), while the moisture content decreased from 21.580% in K0 to 19.425% in K2. Similarly, ash content increased markedly from 0.090% in K0 to 1.855% in K2, whereas crude fat content decreased from 12.635% in the control to 1.390% in the fortified sample. Although carbohydrate content remained relatively unchanged, increasing slightly from 59.320% in K0 to 59.475% in K2, crude fibre content increased appreciably from 1.395% in the control sample to 2.585% in the fortified sample. The mineral analysis showed that K0 had higher levels of zinc (0.144±0.000), calcium (175.000±3.932), and iron (5.859±1.081) than K2 (zinc [0.325±0.050], calcium [152.780±3.932], and iron [5.349±0.360]). The vitamin results also showed that provitamin A (1.115±0.021), vitamin B_6 (0.450±0.070), and vitamin C (0.800±0.141) were higher in the fortified sample. This study concludes that fortifying cake products with watermelon rind flour enhances their proximate composition, vitamins, and mineral content and, therefore, recommends its use in pastry production, particularly cakes, to improve their nutritional quality.

Keywords: Cakes, Watermelon rind flour, Food fortification, Sensory evaluation, Nutrient composition

Introduction

Pastries, particularly cakes, are among the most widely consumed baked goods globally, serving as a popular food choice for all age groups, especially children and school-aged adolescents, due to their convenient handling and ready-to-eat nature (Monteiro et al., 2018). They are eaten between meals, primarily for convenience and sensory enjoyment rather than as a main, nutritionally balanced meal, and they lack a fixed time of consumption, such as breakfast, lunch, or dinner (Adegunwa et al., 2014). Traditionally, commercial cakes are produced using 100% refined wheat flour. However, the conventional wheat-based cake products are nutritionally limited, characterised by high caloric density but relatively low amounts of dietary fibre and essential micronutrients, particularly vitamins and minerals (Gisslen, 2018; Monteiro et al., 2018).

Over-reliance on refined wheat flour not only restricts the utilisation of alternative local crops but also fails to address prevalent nutritional gaps. In developing nations like Nigeria, the consumption of cake products that may be nutritionally deficient can contribute to hidden hunger and childhood undernutrition, which ultimately impairs physical growth and cognitive development (World Health Organisation [WHO], 2024; United Nations Children's Fund [UNICEF], 2023). To improve their nutritional value, food-to-food fortification has been explored as a practical approach for enhancing commonly consumed products by incorporating nutrient-dense plant materials (Oyeyinka & Oyeyinka, 2018).

Food-to-food fortification refers to the incorporation of nutrient-dense, locally available foods into commonly consumed staples to enhance their micronutrient profile (Oyeyinka & Oyeyinka, 2018). It has gained prominence in low- and middle-income countries due to its affordability, accessibility, and potential to improve dietary diversity while maintaining cultural acceptability (Osendarp et al., 2018; Olson et al., 2021). The primary purpose of fortification is to correct micronutrient deficiencies, particularly those involving iron, vitamin A, iodine, and zinc, which remain widespread public health concerns globally (WHO, 2024; Hess et al., 2023). It also serves to restore nutrients lost during processing and enhances sensory qualities such as colour, texture, and flavour, thereby improving the overall acceptability and consumption of fortified foods (Nagar et al., 2018; Huey et al., 2023). Food-to-food fortification strategy leverages indigenous crops and underutilised food resources that are naturally rich in fibre, vitamins, minerals, and bioactive compounds, thereby reducing reliance on synthetic fortificants (Oyeyinka & Oyeyinka, 2018). One potential but underutilised fortificant is watermelon rind flour, which offers both nutritional and functional benefits.

Watermelon (*Citrullus lanatus*) is a tropical fruit belonging to the family Cucurbitaceae, cultivated widely in warm regions such as Nigeria and Ghana (Ministry of Food and Agriculture, 2017). The fruit consists of three major components: the flesh, seeds, and rind, with the rind accounting for approximately one-third of the total fruit weight (Ben Romdhane et al., 2024). The rind, though often discarded, is edible and has been traditionally consumed in various forms; for instance, it is sliced, dried, and cooked in parts of Africa, while pickled rind is consumed in some regions of the USA (Okonma et al., 2011). Importantly, studies (Ashoka et al., 2022; Erukainure et al., 2010; Gladvin et al., 2017) have demonstrated that watermelon rind contains significant amounts of nutrients, including vitamins A (52.13 mg/100 g), C (8.46 mg/100 g), and B6 (5.34 mg/100 g), as well as minerals such as potassium (1.37 mg/100 g), zinc (1.29 mg/100 g), and magnesium (1.48 mg/100 g). In addition, it is a good source of dietary fibre and contains bioactive compounds such as citrulline, an amino acid involved in arginine synthesis (Oyeleke et al., 2012). These nutritional properties suggest that watermelon rind could serve as a valuable ingredient for improving the micronutrient composition of food products, such as cake. Beyond its nutrient content, watermelon rind has been reported to contain structural polysaccharides such as cellulose, hemicellulose, and pectin, as well as bioactive compounds including carotenoids and phenolic compounds (Al-Sayed & Ahmed, 2013; Ben Romdhane et al., 2024). These components contribute to its functional properties and potential applications in food systems, particularly in enhancing texture, fibre content, and overall nutritional quality.

However, despite this demonstrated functional potential, the large-scale utilisation of watermelon rind remains limited, as it is still discarded as waste, contributing to significant post-harvest losses and environmental concerns (Okonma et al., 2011). Studies (Al-Sayed & Ahmed, 2013; Ashoka et al., 2022) have highlighted its potential for value addition when incorporated into food products, such as flour-based goods. This aligns with the need to diversify raw materials used in baking, as heavy reliance on wheat flour limits the use of locally available, nutrient-rich alternatives (Ikuomola et al., 2017). The implication is that using watermelon rind as flour might offer a cost-effective way to fortify cakes with fibre and micronutrients while reducing food waste.

Additionally, the incorporation of composite flours can alter the sensory properties of baked goods. The sensory attributes of a food product, specifically appearance, texture, aroma, and taste, are the primary determinants of consumer acceptability (Civille & Carr, 2015). Consumer preference is largely determined through sensory evaluation, where panellists observe and report their responses to food products (Nnam et al., 2024). If a fortified product possesses an exceptional nutritional profile but fails to maintain desirable sensory attributes, consumers are unlikely to accept or purchase it again (Civille & Carr, 2015; Nnam et al., 2024). Therefore, when developing fortified pastries, finding the optimal substitution level that balances nutritional enrichment with high sensory acceptability is critical. Given the widespread consumption of cakes and their potential as vehicles for nutrient delivery, fortifying them with watermelon rind flour presents an opportunity to enhance their nutritional profile while utilising an underexploited agricultural byproduct. Therefore, this study aims to determine the nutrient composition and sensory properties of pastries fortified with watermelon (*Citrullus lanatus*) rind flour.

Objectives of the study

The specific objectives of the study were to determine the:

1. sensory properties (colour, texture, aroma, taste and general acceptability) of cake fortified with different ratios of watermelon rind flour;
2. proximate composition (crude protein, crude fibre, fat, ash, moisture, carbohydrate) of the most acceptable cake sample;
3. vitamin (pro-vitamin A, C and B_6) content of the most acceptable cake sample; and
4. mineral (Zn, Fe and Ca) content of the most acceptable cake sample.

Materials and Methods

Study design: The study adopted a quasi-experimental research design. The approach is particularly suitable for food and nutrition studies, where controlled manipulation of formulations is required but random assignment of subjects to treatment and control groups is not feasible (Creswell & Creswell, 2018). This design enabled the researchers to deliberately assign treatments based on predetermined criteria, such as formulation type, while still allowing for systematic comparison of outcomes.

Procurement of raw materials: Watermelon fruit, all-purpose flour, sugar, butter, eggs, baking powder, salt, milk, and vanilla extract were obtained from Ogige Main Market in Nsukka Local Government Area, Enugu State.

Sample preparation: The watermelon rinds were processed into flour using standard procedures. First, the entire watermelon was thoroughly washed under running water to remove sand particles and adhering dirt, and then the rind was separated from the pulp. Using a clean stainless-steel knife, the green outer skin was carefully peeled off, leaving only the white portion of the rind. The white rinds were then cut into small, uniform pieces to ensure even dehydration. The sliced rinds were arranged on dehydrator trays and dried in a hot-air oven at 60 °C for approximately 12 hours. The dried rinds were milled using a laboratory hammer mill (Thomas Willey Mill Model ED-5, USA) to obtain a fine flour. The flour was sieved through a 1 mm mesh screen to achieve a uniform particle size and stored in airtight containers until further use.

Formulation of flour blends: Composite flours were produced by blending wheat flour with watermelon rind flour at varying proportions according to the specified formulation ratios. One hundred per cent (100%) wheat flour served as the control sample and was coded K0. Other formulations consisted of wheat flour and watermelon rind flour in the ratios 80:20 (K1), 70:30 (K2), and 60:40 (K3). The flour blends were thoroughly mixed in a Kenwood blender (Model BLP40.0WH, Kenwood Ltd., United Kingdom) for 5 minutes at medium speed to ensure complete particle homogeneity before further use.

Recipe for cake production: Cake samples were prepared using the standard recipe described by Alozie et al. (2009), which used 200 g of flour as the base ingredient. This was combined with 120 g of butter, 80 g of sugar, 195 g of beaten eggs, and 60 ml of milk. Salt (2 g) was added, and baking powder (5 g) was incorporated as the leavening agent. This recipe served as the reference formulation for all cake samples.

For the control cake sample (K0), 200 g of wheat flour was used without the addition of watermelon rind flour. In sample K3 (60:40), wheat flour was reduced to 120 g and supplemented with 80 g of watermelon rind flour. Sample K2 (70:30) contained 140 g of wheat flour and 60 g of watermelon rind flour, while sample K1 (80:20) was prepared using 160 g of wheat flour and 40 g of watermelon rind flour.

Cake sample production: For each cake sample, all ingredients were measured and set aside. Butter and sugar were creamed together in a stainless-steel bowl with a wooden spoon until they formed a light and fluffy batter. Beaten eggs and milk were gradually added and mixed thoroughly. The batter was divided into four equal parts in separate bowls. The different ratios of the flour mixtures, previously sieved through a 1 mm mesh sieve with baking powder and salt, were added to the different bowls of batter and mixed thoroughly. In all cake samples, butter was maintained at 120 g, milk at 60 ml, sugar at 80 g, salt at 2 g, eggs at 195 g, and baking powder at 5 g. No vegetable oil, vanilla flavour, or nutmeg was added to any of the formulations in order to ensure consistency across samples and to allow for accurate assessment of the effects of watermelon rind flour inclusion. The batter was poured into greased queen cake baking tins and baked in a preheated oven at 220 °C for 20 minutes. After baking, the cakes were removed from the tins and allowed to cool at room temperature (20–25 °C) for 15 minutes. The cakes were then packaged in airtight glass containers and stored for subsequent analyses.

Sensory evaluation: Cake samples were evaluated to determine the consumer acceptability of their colour, flavour, taste, texture, and overall acceptability. A total of 30 panelists participated in the evaluation. The samples were coded (K0, K1, K2, and K3) and presented in a randomised order to avoid bias. A nine-point hedonic scale was used, where 1 = dislike extremely and 9 = like extremely. Panelists were asked to evaluate each sample independently based on the stated attributes. The overall acceptability score was determined by averaging the panelists' general preferences for each sample, taking into account all sensory attributes. This parameter was used to identify the most acceptable formulation. Based on the sensory evaluation profiles, the composite cake sample that achieved the highest overall acceptability score, along with the control sample, was selected to proceed to the nutritional and chemical analysis phase.

Proximate analysis: Proximate analysis of the cake samples was carried out to determine moisture, crude protein, crude fat, ash, crude fibre, and carbohydrate contents using standard methods of the Association of Analytical Chemistry [AOAC] (2010). Moisture assessed by oven drying, fat by Soxhlet extraction, protein by the micro-Kjeldahl method, ash by muffle furnace incineration, crude fibre by acid–alkali digestion, and carbohydrate calculated by difference. All analyses were conducted in duplicate.

Mineral analysis: Iron, calcium, and zinc contents of the cake samples were determined using AOAC (2010) methods. Iron was analysed spectrophotometrically, calcium by EDTA titration, and zinc using atomic absorption spectrophotometry.

Vitamin analysis: The vitamin content of the cake samples was determined using standard laboratory procedures. Vitamin C (ascorbic acid) was determined according to the AOAC (2010) method using the 2,6-dichlorophenol indophenol titration technique. Specifically, Vitamin B_6 (pyridoxine) content was determined by High-Performance Liquid Chromatography (HPLC) at a flow rate of 1.0 mL/min, with detection against a pyridoxine standard. Pro-vitamin A (β-carotene) was determined using the Harborne (1973) method, as described by Nagata et al. (2007), with absorbance readings at 450 nm used to calculate the quantity.

Data and statistical analysis: The data were analysed using IBM-SPSS, version 22.0. Results obtained through descriptive analysis were expressed as mean ± standard deviation. One-way Analysis of Variance (ANOVA) was used to assess variations across all formulations, and Duncan's Multiple Range Test (DMRT) was applied specifically for mean separation of the sensory evaluation data to determine which blends were significantly preferred by the panelists. Independent-samples t-tests were used to determine significant differences between the control (K0) and the primary fortified sample (K2) for proximate, mineral, and vitamin content. Statistical significance was accepted at $p < 0.05$.

Results

Sensory properties of cake fortified with watermelon rind flour

The results revealed that the incorporation of watermelon rind flour significantly influenced all sensory attributes evaluated ($p < 0.05$). Significant differences were observed in colour ratings ($p < 0.01$), with the control sample (K0; 7.50 ± 1.57) and K3 (7.30 ± 1.75) receiving similarly high scores, whereas K1 (5.33 ± 2.09) and K2 (5.67 ± 1.75) were rated significantly lower. For flavour, significant differences were also recorded ($p < 0.001$), with K3 attaining the highest mean score (7.93 ± 1.41), followed by K2 (6.90 ± 1.81) and the control sample K0 (6.37 ± 2.17), while K1 (5.87 ± 2.00) received the lowest rating. Taste scores differed significantly among the samples ($p < 0.001$). Sample K2 (7.77 ± 1.25) achieved the highest rating, followed by K1 (7.17 ± 1.68) and the control sample K0 (7.07 ± 1.44), whereas K3 (5.07 ± 2.20) recorded the lowest score. Similarly, texture ratings varied significantly ($p < 0.001$), with K1 (7.67 ± 1.65) receiving the highest score, closely followed by K0 (7.33 ± 1.86). Lower texture ratings were observed for K2 (6.40 ± 1.71) and K3 (5.40 ± 1.98). Significant differences were also found in overall acceptability ($p < 0.05$). The control sample K0 (7.93 ± 1.02) was the most preferred, while among the watermelon rind flour-substituted samples, K2 (6.90 ± 1.30) exhibited the highest acceptability, followed by K3 (6.60 ± 2.16). Sample K1 (5.17 ± 2.53) was the least acceptable.

Sample K2 was the regarded as the most accepted sample.

Table 1: Sensory properties of cake fortified with watermelon rind flour

Coded Samples	Colour	Flavour	Texture	Taste	Overall acceptability
K0	7.50 ± 1.57^{a}	6.37 ± 2.17^{ab}	7.33 ± 1.86^{a}	7.07 ± 1.44^{a}	7.93 ± 1.02^{a}
K1	5.33 ± 2.09^{c}	5.87 ± 2.00^{b}	7.67 ± 1.65^{a}	7.17 ± 1.68^{a}	5.17 ± 2.53^{c}
K2	5.67 ± 1.75^{bc}	6.90 ± 1.81^{a}	6.40 ± 1.71^{b}	7.77 ± 1.25^{a}	6.90 ± 1.30^{b}
K3	7.30 ± 1.75^{a}	7.93 ± 1.41^{a}	5.40 ± 1.98^{c}	5.07 ± 2.20^{b}	6.60 ± 2.16^{b}

K0 = cake made from 100% wheat flour (control sample); K1 = cake made from 80% wheat flour, 20% watermelon rind flour; K2 = cake made from 70% wheat flour, 30% watermelon rind flour; K3 = cake made from 60% wheat flour, 40% watermelon rind flour. Means with different superscript letters in the same column are significantly different ($p < 0.05$).

Proximate composition of cakes fortified with watermelon rind flour

Table 2 presents the proximate composition of the control cake (K0, 100% wheat flour) and the composite cake fortified with watermelon rind flour (K2, 70:30 wheat-to-watermelon rind ratio). The incorporation of watermelon rind flour led to notable changes in the cakes' nutritional composition. A significant ($p = 0.007$) reduction in moisture content was observed, decreasing from 21.580% in K0 to 19.415% in K2. In contrast, protein content increased slightly from 4.925% (K0) to 5.280% (K2), and this difference was statistically significant ($p = 0.045$). Marked improvements were observed in both ash and crude fibre content, indicating higher mineral and dietary fibre levels. Ash content increased substantially from 0.090% in K0 to 1.855% in K2 ($p = 0.002$), while crude fibre rose from 1.395% to 2.585% ($p = 0.013$). Conversely, crude fat content showed a significant ($p < 0.001$) decrease from 12.635% in the control sample to 11.390% in the composite cake, as confirmed by the paired sample t-test. Finally, carbohydrate content increased slightly from 59.320% in K0 to 59.475% in K2, with the difference being statistically significant ($p = 0.021$).

Table 2: Proximate composition of cakes fortified with watermelon rind flour

Samples	Protein	Moisture	Ash	Crude fat	Crude fiber	Carbohydrate
K0	4.925±0.021	21.580±0.057	0.090±0.000	12.635±0.021	1.395±1.007	59.320±0.056
K2	5.280±0.014	19.415±0.021	1.855±0.007	11.390±0.014	2.585±0.007	59.475±0.064
p-values	0.045*	0.007*	0.002*	0.013*	0.000*	0.021*

Key: K0 = 100% wheat flour; K2 = 70% wheat flour and 30% watermelon rind flour; *; p-values are statistically significant

Vitamin composition of cakes fortified with watermelon rind flour

Table 3 presents the vitamin composition of cakes fortified with watermelon rind flour.

The results show an increase in vitamin content in the fortified sample (K2) compared with the control (K0), although the difference was not statistically significant. Provitamin A content increased from 0.840 mg/100 g in the control sample (K0) to 1.115 mg/100 g in K2; however, this difference was not statistically significant ($p = 0.081$). Similarly, vitamin B6 content was higher in K2 (0.450 mg/100 g) than in K0 (0.200 mg/100 g), but the difference was not significant ($p = 0.126$). A comparable trend was observed for vitamin C, where the fortified sample (K2) recorded a higher value (0.800 mg/100 g) than the control (0.350 mg/100 g), although the difference was not statistically significant ($p = 0.070$).

Table 3: Vitamin composition (mg/100g) of cakes fortified with watermelon rind flour

Samples	Pro-vitamin A	Vitamin B_6	Vitamin C
K0	0.840±0.02	0.200±0.000	0.350±0.070
K2	1.115±0.021	0.450±0.070	0.800±0.141
p-values	0.081	0.126	0.070

Key: K0 = 100% wheat flour; K2 = 70% wheat flour and 30% watermelon rind flour; Values are mean ± SD; values with different superscripts along a column are significantly different ($p < 0.05$)

Mineral composition of cakes fortified with watermelon rind flour

Table 4 presents the mineral composition of cakes fortified with watermelon rind flour. The results indicate variations in mineral content between the control sample (K0) and the fortified samples, although these differences were not statistically significant. The zinc content decreased from 0.325 mg/100 g in the control sample (K0) to 0.114 mg/100 g in K2; however, this difference was not statistically significant ($p = 0.123$). In contrast, the calcium content increased from 152.780 mg/100 g in K0 to 175.000 mg/100 g in the fortified sample, indicating an improvement, although the difference was not statistically significant ($p = 0.156$). A similar trend was observed for iron content, with K2 recording a slightly higher value (5.859 mg/100 g) than the control (5.349 mg/100 g). This difference was also not statistically significant ($p = 0.705$). Overall, while incorporating watermelon rind flour influenced the mineral composition of the cakes, the observed changes were not statistically significant at the level of substitution studied.

Table 4: Mineral composition (mg/100g) of cakes fortified with watermelon rind flour

Samples	Zinc	Calcium	Iron
K0	$0.325±0.050^{a}$	$152.780±3.932^{a}$	$5.349±0.360^{a}$
K2	$0.144±0.000^{a}$	$175.000±3.932^{a}$	$5.859±1.081^{a}$
p-values	0.123	0.156	0.705

Key: K0 = 100% wheat flour; K2 = 70% wheat flour and 30% watermelon rind flour; Values are mean ± SD; SD; values with different superscripts along a column are significantly different ($p < 0.05$)

Discussion

Sensory properties of cake made from watermelon rind flour

The sensory attributes (colour, texture, flavour, taste, and overall acceptability) of cakes fortified with watermelon rind flour were evaluated using a 9-point hedonic scale. The results showed that the incorporation of watermelon rind flour significantly ($p < 0.05$) influenced all sensory characteristics. The control and 40% substitution samples had similarly high colour ratings, while intermediate levels were less preferred, suggesting that higher inclusion of watermelon rind flour may enhance visual appeal, likely due to increased pigment concentration. The colour ratings observed in this study were slightly higher than those reported by Eke-Ejiofor (2013) for cakes produced from African breadfruit and sweet potato-wheat composite flour blends, suggesting improved colour retention in samples made with watermelon rind. Colour is a critical quality attribute in sensory evaluation, as it often reflects product stability and overall quality and can strongly influence consumer perception (Kardas et al., 2024). In terms of flavour, significant differences were observed among samples, with higher substitution levels receiving better scores than the control and lower substitution levels. This improvement may be linked to the presence of natural flavour compounds in watermelon rind flour as previously observed by Al-Sayed and Ahmed (2013). A similar trend was reported by Anyaeche (2021), who noted that composite flours can enhance flavour profiles, although with lower overall ratings in banana-peel-based cakes. Flavour remains a key determinant of product appeal before and during consumption.

For taste, moderate substitution levels were rated more favourably than both the control and the highest substitution level, while excessive inclusion resulted in lower acceptability. These findings are consistent with those of Eke-Ejiofor (2013), who also reported moderate taste scores for composite cakes prepared from African breadfruit and sweet potato-wheat flour blends. The results suggest that while partial substitution can improve palatability, excessive incorporation may negatively affect taste. Regarding texture, moderate inclusion levels produced scores comparable to the control, whereas higher substitution levels resulted in lower ratings. Although slightly lower than those reported by Sampson and Abiire (2025) for orange-fleshed sweet potato cakes, the findings indicate that moderate incorporation of watermelon rind flour does not compromise textural quality. Texture is critical to product quality, as it is influenced by the interaction between gluten and fibrous components in composite flours. Regarding acceptability, the control sample remained the most preferred. However, among the fortified samples, moderate substitution demonstrated better acceptance than both lower and higher inclusion levels. This suggests that while watermelon rind flour can enhance certain sensory attributes, optimal acceptability is achieved at moderate levels of substitution. Overall, the findings indicate that moderate inclusion of watermelon rind flour improves key sensory attributes such as taste and overall acceptability, whereas excessive substitution may adversely affect texture and palatability despite enhancing flavour.

Proximate composition of cake fortified with watermelon rind flour

The protein content of the fortified sample was higher than that of the control, likely due to the inclusion of watermelon rind flour in the formulation. However, the protein levels observed were lower than those reported by Sampson and Abiire (2025) for cakes produced from orange-fleshed sweet potato blends. This variation is likely due to differences in the intrinsic protein composition of the raw materials used, as watermelon rind generally contains less protein than some other plant-based fortificants. The moisture content of the control cake was higher than that of the fortified sample. The reduced moisture level in the fortified cake suggests improved shelf stability, as lower moisture content limits microbial growth and delays spoilage during storage. This finding agrees with reports by Tortoe et al. (2017) and Korese et al. (2021), who observed a decrease in moisture content in baked products with increasing levels of plant-based flour substitution, attributed to the distinct water-binding characteristics of fibre and starch in these materials. Ash content, which reflects the total mineral composition, was significantly higher in the fortified sample than in the control, indicating that watermelon rind flour contributed to the cake's mineral content. In contrast, crude fat content was lower in the fortified sample, a reduction that may be associated with the high fibre content and water-binding capacity of watermelon rind flour, which can dilute fat concentration in the final product. This observation is consistent with Sampson and Abiire (2025), who also reported a decline in fat content in composite cake formulations.

Crude fibre content was higher in the fortified cake, confirming that watermelon rind flour is a good source of dietary fibre. The fibre levels obtained exceeded those reported by Olamiti and Ramashia (2024) and were comparable to those reported by Khatun and Asaduzzaman (2025), who observed increased fibre content in products formulated with biofortified flours. This enhancement is nutritionally beneficial, as dietary fibre plays an important role in digestive health. The carbohydrate content of the fortified sample was slightly higher than that of the control, indicating that the fortified cake remains a good source of energy. This is in agreement with the findings of Tortoe et al. (2017), who reported that the inclusion of plant-based composite flours, such as watermelon rind flour, can increase the energy density of composite baked products. Overall, incorporating watermelon rind flour improved the cake's nutritional quality, particularly by enhancing fibre and mineral content, while also contributing to reduced moisture and fat levels.

Vitamin composition of cake fortified with watermelon rind flour

The increase in vitamin content observed in cakes fortified with watermelon rind flour is consistent with reports that processed underutilised plant materials can serve as important sources of micronutrients when appropriately incorporated into food products. For instance, Oguejiofor et al. (2022) reported improved concentrations of vitamins and minerals in processed underutilized plant materials, emphasising the role of food processing in enhancing nutrient density. In the present study, the provitamin A content was significantly higher in the composite sample than in the control sample, indicating that enrichment with watermelon rind flour effectively increased the cake's provitamin A content. This finding aligns with the results of Mofunanya et al. (2024), who observed that incorporating watermelon rind flour into wheat flour bread enhanced its nutritional and antioxidant properties, particularly by increasing vitamin A levels. Similarly, the vitamin B6 content of the fortified sample was higher than that of the control, further demonstrating the nutritional benefit of incorporating watermelon rind flour. This agrees with the findings of Khan (2025), who reported a significant increase in vitamin B6 content when wheat flour was supplemented with watermelon rind flour. The vitamin C content of the fortified cake also exceeded that of the control sample, confirming that watermelon rind flour contributes positively to vitamin C fortification. This observation supports the findings of Ashoka et al. (2022), who reported a significant increase in vitamin C content when watermelon rind flour was added to wheat flour. Collectively, these findings confirm that watermelon rind flour is a valuable source of vitamins and can be effectively utilised to enhance the micronutrient quality of cake products.

Mineral composition of cake fortified with watermelon rind flour

With respect to mineral composition, zinc content was higher in the control sample than in the fortified sample, indicating that cakes produced from 100% wheat flour contained more zinc than those fortified with watermelon rind flour. In contrast, calcium content increased in the fortified sample, although not significantly, demonstrating the contribution of watermelon rind flour to enhancing the cakes' mineral profile. This finding is consistent with the report by Khan (2025), who also observed a significant increase in calcium content following supplementation with watermelon rind flour, highlighting its potential to improve the nutritional quality of baked products. Similarly, iron content was higher in the fortified sample than in the control, suggesting that the inclusion of watermelon rind flour positively enhances iron levels in the cakes. The observed increases in calcium and iron may be attributed to the naturally high concentration of structural minerals and essential divalent cations present in dehydrated cucurbit rinds, which are retained during processing and incorporated into the baked product. Overall, these results indicate that watermelon rind flour can serve as a valuable ingredient for improving the mineral composition of bakery products, particularly in increasing calcium and iron content.

The observed improvements in nutritional quality highlight the potential of watermelon rind flour as a functional ingredient in cake production. Beyond enhancing nutrient density, using watermelon rind flour is a practical way to reduce food waste, as rinds are typically discarded after the pulp is consumed. The development and consumption of such functional foods may improve nutritional status and support the management of degenerative diseases associated with micronutrient deficiencies.

Conclusion

This study demonstrated that incorporating watermelon rind flour into wheat-based cake formulations significantly influences the physicochemical properties and nutritional quality of the final product. The results indicate that watermelon rind flour can be effectively incorporated at substitution levels of 10–30% to produce cakes with improved nutritional profiles while maintaining acceptable sensory qualities. This optimal range is supported by sensory evaluation findings showing that higher substitution levels (40%) negatively affected texture and taste, whereas formulations within the 10–30% range retained good consumer acceptability. Among the fortified samples, the 70:30 wheat-to-watermelon rind formulation provided the best balance between enhanced taste and overall acceptability, while the 80:20 formulation exhibited superior textural properties to the control. Furthermore, the study highlights the potential for value-added utilisation of watermelon rind, typically regarded as agricultural waste, by incorporating it into commonly consumed products such as cakes. The findings therefore support the use of watermelon rind flour as a sustainable ingredient in bakery formulations, offering a practical approach to improving nutritional quality, reducing agro-industrial waste, and enhancing dietary nutrient intake.

Recommendations

The following recommendations were made based on the study's findings.

1. Food manufacturers should incorporate watermelon rind flour at a 30% substitution level (70:30 wheat to rind flour), as this ratio provides improved nutritional quality, particularly in fibre, minerals, and vitamins, while maintaining acceptable sensory characteristics.
2. Nutritionists and policymakers should consider incorporating watermelon rind flour–fortified products into school feeding and public health programmes as a cost-effective strategy to alleviate micronutrient deficiencies among vulnerable populations.
3. Stakeholders in the food industry should promote the use of watermelon rind flour as a sustainable ingredient, encouraging its processing and utilisation to reduce food waste and enhance the nutritional value of widely consumed bakery products.

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Economic Effects of Artificial Intelligence (AI)-Driven Mechanisation on Farm Labour in Nigeria's Agricultural Sector: A Conceptual Review

Nwokah, O. B[1]., Morgan, N. C.,[1]& Obiene, M. M[1].
[1]Department of Agricultural Economics Extension and Rural Development, Niger Delta University, Wilberforce Island, Bayelsa State.
*Corresponding author's email: oyeindoubrabethel@ndu.edu.ng
ORCID number:0009-0007-8980-7959
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Abstract

The review brings to light the economic effects of AI-driven mechanization on farm labour in Nigeria's agricultural sector. The review is organized as an overview of AI-driven mechanization in the Nigerian agricultural sector, key AI mechanization technologies in Nigeria and their applications, economic effects of AI on farm labour and challenges to the use of AI-driven mechanization in the Nigerian agricultural sector. Artificial Intelligence (AI) is poised to transform farming by reducing labour needs while increasing food production. As AI automation progresses, it is expected to gradually replace human labour, particularly on farms, where robots and autonomous machines will manage operations and utilize predictive analytics for decision-making. The adoption of new technology and mechanization in agriculture can significantly enhance food production. However, it warns that the implementation of AI might lead to challenges such as unemployment among unskilled labourers. Additionally, inadequate connectivity in rural areas could hinder AI effectiveness. Recommendations include improving connectivity and infrastructure, training extension personnel on AI, and making agriculture more appealing to youth, especially graduates.

Keywords: Artificial Intelligence, Mechanization, Farm Labour, Agricultural Sector

Introduction

According to the United Nations Department of Economic and Social Affairs (UNDESA, 2019), Nigeria holds the title of the most populous country in Africa, with an estimated population of approximately 200 million people, making it the sixth most populous nation globally. This large population is experiencing rapid growth, evidenced by an annual growth rate of 2.5%, which positions Nigeria to potentially double its population within the next 30 years and ascend to the status of the third most populous country in the world (UNDESA, 2019) Despite this demographic expansion, Nigeria's economy has faced notable adversity in recent years, primarily due to falling oil prices and the impacts of the COVID-19 pandemic. The economic contraction, however, began to show signs of recovery in the fourth quarter of 2020 (Shola et al., 2021). However, key sectors of the Nigerian economy, particularly the agricultural sector, still lack significant technological innovation, which may hinder sustainable economic growth moving forward (Shola et al., 2021)

Agriculture remains a linchpin of Nigeria's economy. Currently, agriculture contributes 23.16-25.87% to real GDP and grew by 0.07% year-on-year in Q1 2025, contributing 23.33% to aggregate GDP; employment in agriculture was 34.31% in 2023 (Nigerian Bureau of Statistics (NBS), 2025). 5). The sector accounts for 34.31% of employment, though other estimates put employment at 70% of households or roughly 140 million people (Food and Agriculture Organization (FAO), 2023). It provides food security, raw materials for agro-allied industries, foreign exchange earnings, and a market for industrial products. Crop production dominates the sector, accounting for 66.76% of its nominal value (NBS, 2025). Before the discovery of crude oil in 1956, Nigeria was an agrarian economy and global agricultural powerhouse. In the 1960s, the country controlled 42% of global groundnut oil trade, 27% of world palm oil, and 18% of cocoa trade (FAO, 2023). Agriculture was the major source of foreign exchange through exports of groundnuts, cocoa, palm oil, rubber, and hides/skins; food was abundant, and Nigeria was self-sufficient, with agricultural exports accounting for over 70% of total exports in 1960 (Shaibu, 2023). The oil boom of the 1970s shifted government focus to petroleum because of shorter-term profits. Agriculture's share of GDP fell from 60% in 1960 to less than 10% by 1978, and Nigeria moved from food self-sufficiency to a net food importer; trend analysis shows a steady downward GDP share in 1960-1969, stagnation during 1970-1985, and a slight recovery from 1986 to 2020 with policy interventions (Shaibu, 2023). Crop production constitutes the major agricultural activity, with key staples such as rice, maize, sorghum, millet, cowpea, yam, and cassava experiencing increased production in 2025 relative to 2024, largely due to improved agricultural inputs and government support programmes (FAO, 2023). However, this growth has not translated into food self-sufficiency, as Nigeria remains a net food importer; between 2016 and 2019, agricultural imports were valued at ₦3.35 trillion, exceeding exports valued at ₦803 billion by more than fourfold (FAO, 2023).

Recent studies identified overlapping structural, economic, and security challenges. Insecurity such as banditry, insurgency, and farmer-herder clashes have displaced farmers, especially in the major agrarian states such as Benue and Borno. Over 1,356 farmers were killed between 2020 and 2024, and many fields remain uncultivated as families flee during planting season (Awakessien, 2026). In Benue, Nigeria's "Food Basket" state, farmers have lost billions in investments, and many have abandoned their farms entirely (Awakessien, 2026). Structural and economic challenges further constrain the growth of Nigeria's agricultural sector. Although agriculture remains a vital contributor to the country's GDP and a major source of employment, it is largely dominated by smallholder and subsistence farming systems, which limit productivity and commercialization. Nevertheless, the adoption of artificial intelligence (AI) technologies holds considerable potential to transform the sector by improving productivity, resource efficiency, decision-making, and overall agricultural sustainability.

Objectives of the Review: This paper focuses on evaluating the economic effects of AI-driven mechanization on agricultural labour in Nigeria. The paper specifically focused on;

i. the overview of AI-driven mechanization in Nigerian agricultural sector;
ii. key AI mechanization technologies in Nigeria and their applications;
iii. economic effects of AI on farm labour, and;
iv. challenges to the use of AI driven mechanization in Nigerian agricultural sector.

Methodology

The articles that were included in this review were obtained from peer-reviewed academic journals, government reports and institutional databases such as Food and Agriculture Organization (FAO), International Institute for Tropical Agriculture (IITA). Literature was sourced from Google Scholar and Elicit using keywords from the review topic. Articles were selected based on relevance to the review topic.

Overview of AI-Driven Mechanization in the Nigerian Agricultural Sector

Artificial Intelligence (AI) refers to the ability of machines to replicate intelligent human behaviour, involving the creation of algorithms and systems capable of executing tasks such as visual perception, speech recognition, decision-making, and language translation (Russell & Norvig, 2020). In the agricultural sector, AI encompasses machine learning, computer vision, and data analytics to enhance farming practices, boost crop yields, and optimize resource utilization. This includes the utilization of AI-driven drones, crop monitoring sensors, predictive analysis for weather, pest and soil conditions, and automated machinery powered by AI for tasks like planting and harvesting (Mcintosh, 2021). These technologies are designed to enhance and exceed natural processes while being grounded in them, affecting all areas of agricultural management, including propagation, cultivation, livestock management, crop health, pest control, harvesting, and yield optimization.

The emergence of AI during the 4th Industrial Revolution presented both significant prospects and challenges for developing nations, including Nigeria. While AI has the potential to enable these countries, particularly in the "global south," to accelerate their development and achieve substantial economic growth, potentially contributing more than US$15 trillion to the global economy, there is a prevailing concern that these benefits may not be equitably distributed. Without intentional policies, strategic actions, and cooperation among key stakeholders, developing countries may find themselves at risk of being left behind in this technological advancement (Schwab, 2016; Price Waterhouse Coopers [PWC], 2017).

Artificial Intelligence (AI) has emerged as a transformative technology that holds the potential to significantly reshape the processes surrounding agricultural knowledge. AI-driven mechanization in Nigerian agriculture refers to the integration of advanced technologies such as machine learning, robotics, and the Internet of Things (IoT) to automate traditional farming processes (Kolawole, 2024). It influences how this knowledge is generated, processed, and disseminated to farmers. The applications of AI in agriculture cover a wide range of functionalities, including predictive analytics that assist in estimating crop yields, computer vision technologies that aid in the detection of pests and diseases, and machine learning algorithms designed to optimize the use of fertilizers and irrigation systems (Adeyemi et al., 2025). Furthermore, natural language processing tools play a critical role in facilitating personalized communication between farmers and agricultural experts; collectively, these AI applications contribute to more efficient, informed, and responsive agricultural practices, thereby enhancing productivity and sustainability in the agricultural sector (Ojo et al., 2020)

Globally, agricultural advisory services are integrating AI-driven platforms that leverage real-time environmental and agronomic data to offer tailored recommendations for farmers. This evolution aims to enhance decision-making accuracy and mitigate climate-related risks. In sub-Saharan Africa, various innovative digital tools, including Precision Agriculture for Development (PAD), eSoko, and IBM's Agrolink, are emerging to support smallholder farmers. (Adeyemi et al., 2025) These tools deliver critical information such as automated messages, market updates, and crop management strategies directly to farmers through mobile phones and voice systems in their native languages (Bulus et al., 2021). Nigeria is also embracing this technological shift, exemplified by platforms like Zenvus and Hello Tractor, which utilize AI to boost agricultural productivity by providing farmers with vital data regarding soil conditions, rainfall forecasts, mechanization schedules, and pest occurrences, these platforms integrate satellite imagery, sensor data, and machine learning models to produce actionable and economically feasible insights (Ojo et al., 2020) This shift is critical for Nigeria, where the agricultural sector employs over 60–70% of the population but remains hampered by low productivity and climate vulnerability (Kolawole, 2024).

Key AI Mechanization Technologies in Nigeria and their Applications

The adoption of AI in Nigerian mechanization focuses on transforming static machinery into smart systems that can adapt to environmental data, in the following ways:

i. Precision Tractor-Hailing

Precision tractor is a digital platform that uses Artificial Intelligence of Things (AIoT), Global positioning System (GPS) and mobile applications to connect smallholder farmers with tractor services on demand, operating like Uber services such as Hello Tractor utilize AI and GPS to bridge the mechanization gap (Okamgba, 2025). It addresses Nigeria's low tractor density of 13 tractors per 100km² vs global average of 200 tractors and high reliance on manual labour (Okamgba, 2025). Hello Tractor, founded in Nigeria in 2014, connects tractor owners to farmers and has serviced 2,425 hectares of land with small and medium service support to 3,541 farmers by connecting them to tractor owners via a hailing app (Adamu-Ahmed et al., 2024). The system uses predictive analytics to schedule maintenance and optimise fuel consumption of the tractors; collectively, these platforms shift mechanisation from asset ownership to service access, making precision agriculture financially viable for smallholder farmers and contributing to Nigeria's food security and rural job creation agenda. (Adamu-Ahmed et al., 2024).

ii. Autonomous Aerial Surveillance Mechanisation

Autonomous aerial surveillance is an emerging key AI technology in Nigeria. According to McCarthy et al. (2023), autonomous aerial surveillance uses unmanned aerial vehicles (UAVs), also known as AI-powered drones and satellites, for real-time crop monitoring. This technology is strengthening mechanisation by enabling automated crop monitoring and precision input management for smallholder systems. UAV startups such as AirSmat and Zenvus employ computer vision to detect early signs of disease, nutrient deficiency, and pest invasion; the UAV's have multispectral sensors that can detect crop stress, pests, and nutrient deficiencies several days before visible symptoms, allowing targeted spraying and reducing chemical use (Idu, 2025). In sub-Saharan Africa, studies show pooled disease detection accuracy of 90.2% and yield prediction $R^2 = 0.841$, confirming UAVs are technically ready for deployment even under resource constraints with benefits including early pest detection, input optimisation, and yield forecasting (McCarthy et al., 2023). By integrating autonomous flight planning and edge AI, UAVs shift mechanisation from manual scouting to data-driven, site-specific decisions, improving productivity on farms under 2 hectares without requiring farmer ownership of the technology (Olusanya et al., 2025).

iii. Smart Irrigation and Soil Sensors

Smart irrigation and soil sensors are another key AI mechanisation technology advancing Nigerian agriculture. Smart irrigation systems use IoT controllers, solenoid valves, weather data, and AI algorithms to automate water delivery by analysing soil moisture, crop type, and evapotranspiration to optimise irrigation timing and volume without human input (FAO, 2023). In Nigeria, solar-powered IoT pumps deployed in Kano, Sokoto, and Kebbi address water scarcity and labour shortages while improving water use efficiency under programs by the Federal Ministry of Agriculture and Rural Development (FMARD) and National Agricultural Land Development Authority (NALDA) (Olaniyi et al., 2022).

AI-controlled irrigation systems adjust water flow based on real-time soil moisture and weather patterns; these systems ensure optimal hydration while conserving water resources, which are essential in drought-prone regions. Data for agricultural production are so numerous that it is now possible to standardise and enhance production protocols. (Olusanya et al., 2025). Data is collected using various sources, such as soil sensors, automated irrigation systems, satellite-based imagery, local weather systems, etc., providing actionable insights which help farmers make decisions to improve sustainability, efficiency and profitability (Olusanya et al., 2025). Predictive analytics of these data optimise the potential for healthy crop and livestock production, and data-driven agriculture informs precision farming, which substantially reduces costs and inputs, e.g., water and pesticide application and fuel costs (Olusanya et al., 2025). Soil sensors complement this by measuring moisture, temperature, pH, and NPK, then transmitting data via GSM or LoRa for AI-driven insights on crop health and fertiliser needs (International Institute for Tropical Agriculture (IITA), 2021). Sensor networks enable field studies and precision agriculture demonstrations, while smart irrigation provides data for research on sustainability and climate adaptation (Adeyemi & Idowu, 2020).

iv. Post-Harvest Automation

Post-harvest automation is a critical AI mechanisation technology reducing food loss and improving value chains in Nigeria. It integrates AI-powered sorting, drying, milling, packaging, and cold storage systems that monitor moisture content, detect spoilage, and optimize processing without manual labour (FAO, 2023). In Nigeria, where 30-40% of perishable crops are lost post-harvest, solar-powered cold rooms and automated dryers deployed by NALDA and International Fund for Agricultural Development (IFAD) in Benue, Kaduna, and Oyo states are improving shelf life and market access for tomatoes, cassava, and grains (Adeyemi & Idowu, 2020). AI vision systems now sort fruits by size, colour, and defects, while IoT sensors track temperature and humidity in storage to prevent aflatoxin and waste (IITA, 2021).

In the cassava and palm oil value chains, AI is being integrated into processing lines for intelligent sorting and grading. Using hyperspectral cameras, these systems identify defects and command robotic arms to divert substandard produce (CreedTec, 2025).

Economic Effects of AI on Farm Labour

The integration of Artificial Intelligence (AI) in agriculture is catalysing a shift from labour-intensive traditional farming to capital- and skill-intensive "Precision Agriculture." This transition is characterised by significant productivity gains, structural labour displacement, and a widening wage gap between technical and manual workers. The transition from manual labour to AI-driven automation offers several measurable advantages for the Nigerian landscape:

1. **Task Automation.** The most prominent economic effect is the displacement of routine manual labour, AI-driven systems such as autonomous harvesters and robotic weeding platforms target repetitive, physically demanding tasks. Nigeria’s agricultural sector relies heavily on manual, semi-skilled labour for routine tasks such as weeding, pesticide application, and harvesting (Veriv Africa, 2025). Projections suggest that full adoption of AI in Nigeria’s agriculture could potentially replace the need for

repetitive tasks (Veriv Africa, 2025). AI is increasingly replacing semi-skilled labour in harvesting, sorting, and pesticide application. Research indicates that AI simultaneously displaces routine work while intensifying productivity concentration among leading firms (Datti, 2025). Unlike previous industrial shifts that replaced mechanical tasks, AI now automates cognitive-mechanical tasks like crop health assessment and selective spraying (PWC, 2025).

2. Wage Polarization and the Skill Premium

AI mechanization in Agriculture increases wage polarization and the skill premium for farm labour by automating routine manual tasks while raising demand for tech-savvy workers. Autor et al. (2023) show that automation replaces routine task raising returns for skilled workers, AI is reshaping the agricultural wage structure by creating a skill premium for workers capable of managing digital systems. AI-related skills (e.g., drone operation, data analytics command a significant wage premium. Recent data suggests a 56% wage premium for AI skills globally, up from 25% in previous years (PWC, 2025). Economists distinguish between jobs at high risk of substitution and those with high complementarity, where AI boosts productivity and wages for workers who use the technology to enhance their performance (Pizzinelli, 2024).

3. Productivity and Capital Intensity

AI increases Total Factor Productivity (TFP) by optimizing inputs like water, fertilizer, and labour. Industries highly exposed to AI have seen 3x higher growth in revenue per employee compared to less-exposed sectors (PWC, 2025). In addition, AI models facilitate accurate yield prediction and early disease detection, leading to higher revenues per acre (Datti, 2025). The application of precision also reduces pesticide and fertilizer waste, significantly cutting operating expenses (Agri Business Review, 2024).

4.Regional and Structural Economic Shifts

AI mechanization is causing regional and structural economic shifts in Nigeria farm labour market. Regional labour demand is moving from labour- abundant areas to mechanized areas where AI irrigation, drones and tractors reduce the need for manual labour workers (Olaniyi et al, 2022). This shifts rural-urban migration patterns, farmers now need fewer workers but higher digital literacy which creates wage polarization and forces labour to reskill, the effect is higher productivity per worker (Adeyemi & Idowu, 2020).

Challenges to the Use of AI-Driven Mechanization on Farm Labour in the Nigerian Agricultural Sector

The transition from manual labour to AI-driven automation offers several measurable advantages for the Nigerian landscape. In Nigeria, the adoption of AI-driven mechanization, ranging from autonomous tractors to precision drones, presents a complex paradox, while these technologies offer a solution to Nigeria's low agricultural productivity and high post-harvest losses, they introduce significant structural and socioeconomic challenges to a labour force that currently accounts for approximately 35% of the nation's total employment (Datti, 2025). Challenges of AI-driven mechanization on farm labour in Nigeria include:

1. The Digital Skills Gap and Worker Exclusion

A significant knowledge gap exists between existing traditional farming practices and the technical requirements of AI systems. Most rural smallholder farmers and labourers lack the digital literacy required to interact with AI-powered mobile apps or maintenance software (Eleke et al., 2024). The shift from "manual labour" to "technical management" requires a workforce skilled in data analytics and drone operation, research indicates that without targeted training, Nigeria's youth will be sidelined by high-skill AI systems (International Monetary Fund (IMF), 2026; Omole & Fasina, 2024).

2. Infrastructure and Connectivity Barriers

AI systems are only as effective as the infrastructure supporting them, which is a major bottleneck in Nigeria. AI-driven precision agriculture relies on stable 4G/5G networks and GPS. Inadequate broadband connectivity in rural Nigeria often renders these systems ineffective, creating a digital divide where only farms near urban hubs benefit (Datti, 2025). Also, the lack of a stable electricity supply for charging drones, sensors, and autonomous equipment remains one of the top-ranked barriers to AI adoption in Nigeria (Adegoke et al., 2025).

3. Economic Barriers and Market Consolidation

The high cost of AI-driven mechanization risks concentrating agricultural wealth in the hands of a few. With farm sizes typically averaging 1–2 hectares, the initial investment in AI hardware is economically unfeasible for the average Nigerian farmer (Omole & Fasina, 2024). Studies by Bolana and Oyeyemi (2021) shows that fewer than 10% of smallholder farmers have access to formal agricultural credit needed to adopt modern technologies, forcing them to rely on informal sources with high interest rates and limited capital; about 27% of households are constrained due to collateral demands, low financial literacy and bureaucratic processes often leaving them unable to compete with large agribusinesses that utilize AI to lower unit costs.

4. Socio-Cultural and Security Challenges

AI adoption in Nigeria faces unique local constraints beyond just the technical. Some rural communities view AI as foreign or complex, leading to cultural resistance, especially when AI data-driven insights contradict traditional indigenous knowledge (Ifejesu, 2021). Also, vandalism, theft, and the general insecurity in farming regions (such as farmer-herder conflicts) pose a high risk to expensive AI sensors and machinery left in the field (American University of Nigeria [AUN], 2025).

Conclusion

The study highlights overview of AI-driven mechanization in Nigerian agricultural sector, key AI mechanization technologies in Nigeria and their applications economic effects of AI on farm labour and challenges to the use of AI driven mechanization in Nigerian agricultural sector. As AI automation progresses, it is expected to gradually replace human labour, particularly on farms, where robots and autonomous machines will manage operations and utilize predictive analytics for decision-making. The adoption of new technology and mechanization in agriculture can significantly enhance food production. However, the paper also reveals that implementation of AI might lead to challenges such as unemployment among unskilled labourers. Additionally, inadequate connectivity in rural areas could hinder AI effectiveness.

Recommendations

Based on the findings for this review paper, the following recommendations were made;

1. The government should improve broadband connectivity and infrastructure in rural areas in Nigeria;
2. Agricultural agencies and research bodies should train extension personnel on AI since they are the ones to train farmers on the AI application;
3. The government should make agriculture more appealing to youths, especially graduates in Nigeria by providing credit facilities.

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