The Role of Digital Systems in the Dissemination of Crop Production Technologies and the Effects of Climate-Smart Agricultural Practices on Productivity of Cape Gooseberry in Baringo County

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Abstract

Cape gooseberry *(Physalis peruviana L.)* is a fruit crop native to South America. The crop has documented nutritional, medicinal, and industrial values. In Baringo County, Kenya, the crop grows naturally in the wild. This study evaluated the use of digital technologies and the incorporation of selected climate-smart agricultural practices in introducing cape gooseberry production in Baringo County and determined crop productivity in kilogrammes per acre. The study used participatory action research and a quasi-experimental design. The study sample comprised 120 farming families. Three sub-counties in the county were purposively selected. From each sub-county, the study selected one ward. The sample was distributed equally among the three wards. The study used random sampling to select 40 farming families from each ward. Within each ward, sampled farming families were assigned to four treatments as follows: The first group received crop technologies through digital systems and incorporated climate-smart agriculture; the second group received technologies through digital systems; the third group incorporated climate-smart agriculture and relied on regular extension services; and the last group relied on regular extension services. The farming families received Cape gooseberry seedlings. The data collection instrument was the crop productivity templates. The data were subjected to Analysis of Variance (ANOVA) at the 0.05 level of significance. The major finding was that disseminating Cape gooseberry technologies through digital systems and incorporating climate-smart agriculture results in higher Cape gooseberry productivity. Therefore, the study recommends that agricultural extension systems in Baringo County integrate ICT resources and climate-smart agriculture.

Keywords: Audio-visual, digital farming, mobile app, technology adoption, online training

Introduction

Cape gooseberry *(Physalis peruviana L.)* is a crop that originated in South American countries such as Chile, Peru, Colombia, Venezuela, Bolivia, and Ecuador, and spread to other continents (Bariega, 2014). In Africa, the crop was first introduced in South Africa in the 1770s (Pulles, 2021) and then spread to other countries on the continent, including Kenya (Kioko, 1987; National Research Council, 1989).

The fruit crop has attracted interest because of its nutritional, medicinal, and industrial uses (Bravo & Osorio, 2016). According to Demİr et al. (2014) and Puente et al. (2011), Cape gooseberry contains essential minerals and vitamins with nutritional and medicinal value. Industrially, Cape gooseberry fruits are used to make jam, raisins, and juice (Ramadan & Moersel, 2007), as well as cosmetic products (Popova et al., 2021).

Cape gooseberry plants require fertile, well-drained soil and a moderate to high rainfall during the early stages of growth (Puente et al., 2011). The crop requires very low rainfall as fruits mature (Morton, 1987). High soil fertility favours vegetative growth over production of fruits, leading to low yields and poor quality fruits (El-Tohamy et al., 2009). According to Morton (1987), Cape gooseberry plants become dormant during drought and do not withstand freezing temperatures.

Attempts to grow Cape gooseberry in Machakos, Makueni, and Busia Counties in Kenya have been made, but there is no documentation of the crop's uptake. However, the crop grows wild in forest areas of Mount Elgon, Mount Kenya, Timboroa Forest, Kakamega Forest, the coastal regions of Kenya, and Koibatek Forest in Baringo County (KALRO, 2021; Wasilwa et al., 2021).

In Baringo County, the crop has not been domesticated. The possible reasons for failure of farmers to take up the crop could be: Insufficient awareness of the benefits of the crop; limited promotion and documentation of recommended crop husbandry practices; and bias in research and development in favour of commercial crops (KALRO, 2021). Mungai et al. (2018) and Gichamba et al. (2017) raised concerns about the limited number of extension personnel and weaknesses in linkages between farmers and extension staff. In a study conducted in Baringo, Mungai et al. (2018) identified weak linkages between farmers and extension staff and recommended using digital systems in extension service delivery.

Digital systems include radio and television programmes, websites, information kiosks, blogs, video-conference, farmer call centres, social media, digital villages, documentary audio-visual aids, online training and mobile apps (Asenso-okyere & Mekonnen, 2012). This study purposively selected documentary audio-visual aids, online training and mobile apps. These technologies are considered more effective and efficient at raising farmers' awareness and interest in adopting crop husbandry practices. Authors have noted that the use of audio-visual aids, online training, and mobile apps in agricultural extension systems has helped in overcoming the limitations of traditional, face-to-face methods of farmer training by enhancing efficiency, reach, and effectiveness of agricultural information delivery (Hassan, 1995; Oakley & Garforth, 1985; , 2003; Sani et al., 2021; Santucci, 2005).

Digital systems could address the problems associated with limited domestication of Cape gooseberry in Baringo County by disseminating approved Cape gooseberry technologies and incorporating climate-smart agricultural practices to improve soil quality and health. Therefore, this study aimed to introduce Cape gooseberry production to farming families in Baringo County and determine productivity levels when technologies were disseminated through digital systems and climate-smart agricultural practices were incorporated during crop production.

The study sought to analyse the effects of disseminating approved Cape gooseberry technologies using digital systems and the incorporation of climate-smart agricultural practices on the productivity of Cape gooseberry. The study hypothesised that Cape gooseberry productivity levels were the same when using regular extension services and digital services, with climate-smart agricultural practices.

This study was based on Rogers' (2003) diffusion of innovation theory. The theory is used in agricultural extension services, especially when an extension focuses on adopting a specific practice.

Methodology

Location of the Study

The study was conducted in Baringo County. This is because it is one of the counties where the Cape gooseberry crop grows naturally in forests and fallow lands. The county covers 11,015.3 sq. km and has a population of about 666,763 people, according to the 2019 census (KNBS,

2019). Its geographical coordinates lie between longitudes 35 30' and 36 30' East and latitudes 0 10' South and 1 40' North.

Baringo County has six sub-counties, namely, Baringo Central, Baringo North, Baringo South, Mogotio, Eldama Ravine, and Tiaty. The study purposively selected farming families from wards in three sub-counties: Baringo South, Baringo North, and Eldama Ravine. The wards were Saimo/Kipsaraman in Baringo North, Marigat in Baringo South, and Koibatek in Eldama Ravine.

Target Population

The study's target population was 167,000 farming families in Baringo County and 59,337 farming families in the three sampled wards. The accessible population comprised 14,834 farming families drawn from the three selected wards of Baringo County: Saimo/Kipsaraman Ward in Baringo North Sub-County, Marigat Ward in Baringo South Sub-County, and Koibatek Ward in Eldama Ravine Sub-County. The study focused on farming families aged 18 and above, of either gender, who owned land and practised crop farming, livestock keeping, or mixed farming.

Research Design

The study used participatory action research and a quasi-experimental design. The participatory action research design was chosen because it allowed farming families to learn, practice, and reflect collaboratively. Farming families were expected to modify or drop selected Cape gooseberry farming practices. Finally, the farming families were expected to assume ownership of Cape gooseberry production practices. A quasi-experimental design was selected to document and understand the effects of the interventions on Cape gooseberry productivity.

In participatory action research, the farming families were grouped by intervention. The first group received information on approved Cape gooseberry technologies via digital systems and incorporated climate-smart agriculture. The second group received approved Cape gooseberry technologies via digital systems. The third group incorporated climate-smart agriculture and relied on regular extension services for information on crop husbandry practices. The last group relied on regular extension services.

All groups received Cape gooseberry seedlings and participated in the entire production process. Information on Cape gooseberry production was delivered in local languages. Farming families participated in group discussions after each presentation on agronomic practices. Following each discussion, participants documented their observations, provided feedback, and reflected on the practices presented. Each farming family kept records of the Cape gooseberry production processes and crop yields. The study used a quasi-experimental research design to assess the effects of the interventions.

Sampling Procedure and Sample Size

The study sample was drawn from three sub-counties in Baringo County. One ward was purposively selected from each sub-county. The sample size was determined using the formula;

$$n = \frac{NC^2}{C^2+(N-1)\,e^2}$$ (Nassiuma, 2000).

Where: n = Sample size,
N = Population,
C = Coefficient of variation,
e = Standard error

Nassiuma (2000) indicates that a coefficient of variation of 21%–30% and a standard error of 2%–5% are usually acceptable in surveys and experimental designs. This study used a coefficient of variation of 21% and a standard error of 2%.
Based on the formula, the sample was calculated as follows:

$$n = \frac{14834\ x\ 0.21^2}{0.21^2 + (14834 - 1)\ 0.02^2}$$
$$= 109.44$$

The sample size was adjusted by 10 percent, resulting in an increase of 10.944. The final sample was therefore 109.44 + 10.944 = 120.384. This was rounded off to 120. The accessible population sizes from the three wards were close, and, therefore, the sample of 120 farming families was allocated equally among the three wards. Table 1 shows the distribution.

Table 1: Farming Families Sample Size Distribution by Wards (n=120)

Ward	Target Population	Accessible Population	Sample
Saimo/Kipsaraman	21,300	5,325	40
Marigat	18,555	4,639	40
Koibatek	19,482	4,870	40
Total	**59,337**	**14,834**	**120**

Source: KNBS, 2019.

The 120 farming families were distributed across the study interventions, as shown in Table 2.

Table 2: Sample Distribution per Intervention (n=120)

Interventions	Sample size
Digital Systems and Climate-Smart Agriculture	30
Digital Systems	30
Climate-Smart Agriculture	30
Regular Extension Services	30
Total	**120**

Source: Field Data, 2022.

Instrumentation and Reliability

The data collection instruments were the Farmers' Cape gooseberry productivity template and the Observers' Cape gooseberry productivity template. The researcher used the two instruments for triangulation. The researcher's data and the independent observers' data were analysed using Kuder-Richardson 21 (KR21) to assess reliability.

Data Collection Procedure

The farmers accessed crop husbandry practices through Cape gooseberry online training, the mobile app, and regular extension services. They were then issued with Cape gooseberry seedlings to try on their farms.

During crop production, the team continuously documented farm activities. The team used focus group discussions to collect data and information on concerns raised by farming families. Farming families harvested and weighed ripe fruit every two weeks using a scale, starting three months after planting. They recorded the harvests in kilograms in the designated crop productivity record templates in the presence of the researcher or research assistants.

Data Analysis

Analysis of variance (ANOVA) was used to analyse the data and determine whether there was a statistically significant difference in Cape gooseberry productivity in kilogrammes per acre among the interventions. The data were subjected to mean separation using the least significant difference (LSD) at the 0.05 level of significance, a common approach in agricultural and biological experiments.

Results and Discussions

The Cape gooseberry mean productivities in kilogrammes per acre under the four interventions during production are shown in Table 3.

Table 3: Cape Gooseberry Mean Productivity per Mode of Production (n=86)

Modes of Cape Gooseberry Production	n (86)	Mean	Std. Deviation
Digital systems and climate-smart agriculture	22	1764.70	722.60
Digital systems	20	1249.71	711.57
Climate-smart agriculture	21	1128.50	511.95
Regular extension services	23	535.38	341.75

Source: Field Data, 2022

The results in Table 3 indicate that the group of farming families who received Cape gooseberry technologies through digital systems and incorporated climate-smart agriculture during the production of the crop realized the highest productivity mean of 1764.70 kilogrammes per acre, which is supported by Wasilwa et al. (2021), who indicated that the average Cape gooseberry productivity in kilogrammes per acre in Kenya is 1666.67. According to Erra and Misra (2024), Cape gooseberry productivity depends on farmers' crop management. Therefore, the higher Cape gooseberry productivity mean recorded by the group of farming families who were receiving the crop technologies through digital systems and incorporated climate-smart agriculture could be attributed to the positive effects of timely dissemination of approved Cape gooseberry technologies to the farming families through digital systems and incorporation of climate-smart agricultural practices during crop production.

According to Rogers (2003) and Oakley and Garforth (1985), audio-visual aids are very effective for creating awareness and interest in new agricultural technologies and innovations, since they stimulate interest and attentiveness among farmers. In this study, video cameras were used to capture real live Cape gooseberry farms, products, and a Cape gooseberry processing plant in the neighbouring County of Uasin Gishu. The recorded audio-visual aids demonstrated Cape gooseberry production and the crop's potential benefits to farming families.

Regarding online training, Hemmati and Sefidian (2006), Shon (2002), and Syiem and Raj (2015) argued that integrating online training into agricultural extension services enables the timely dissemination of standardized information and knowledge to farmers, regardless of geographic location. In this study, online training via Zoom was used to train groups of farmers from different Wards, namely Saimo/Kipsaraman Ward in Baringo North Sub-County, Koibatek Ward in Eldama Ravine Sub-County, and Marigat Ward in Baringo South Sub-County, on crop husbandry practices.

Another digital system the farming families used was the Cape gooseberry mobile app. The mobile app enabled the farming families to receive Cape gooseberry production reference resources during the crop production process. This was preceded by guidance on how to use the mobile app, followed by assistance with downloading it to their smartphones. Farmers were instructed to use the mobile app during various Cape gooseberry agronomic practices.

Costopoulou et al. (2016) supported the use of mobile apps in agricultural extension, arguing that agricultural mobile apps provide farmers with reference resources during agricultural production processes.

The climate-smart agricultural practices incorporated by the farming families in this study during Cape gooseberry production included applying farmyard manure and intercropping Cape gooseberry with beans. Studies show that applying organic manure improves soil structure and quality (Eghball et al., 2002; Karami et al., 2012; Smith et al., 1998; Zhang et al., 2020). Additionally, El-Nadi et al. (1995), Mc-Grath et al. (1988), and Mitchell (1992) posit that organic manure increases soil organic matter, which in turn increases soil nutrients required for healthy plant growth and improves soil water-holding capacity. Intercropping with leguminous crops improves soil fertility by fixing atmospheric nitrogen. Mukhala et al. (1999) and Perrone et al. (2020) support this concept, noting that intercropping with leguminous crops provides additional nitrogen to soils.

The findings showed that farming families who received Cape gooseberry technologies through digital systems and incorporated climate-smart agriculture during production achieved the highest mean productivity. Their mean productivity was 1,764.74 kilogrammes per acre. One-way Analysis of Variance (ANOVA) results indicated a statistically significant difference in productivity among the four groups, $F(3.82) = 16.556$, $P < .000$. A post hoc test conducted using Least Significant Difference (LSD) identified the groups of farmers whose Cape gooseberry productivity means were statistically different, as shown in Table 4.

Table 4: Cape Gooseberry Productivity Means Post Hoc Test Results using LSD (n=86)

(I) Group No	(J) Group No	Mean Difference (I-J)	Sig.
Digital + CSA	Digital	514.98895*	.006
Digital + CSA	CSA	636.19569*	.001
Digital + CSA	Regular	1229.31958*	.000
Digital	CSA	121.20674	.512
Digital	Regular	714.33063*	.000
Regular	CSA	-593.12389*	.001

*The mean differences at the 0.05 level of significance.
Source: Field Data, 2022

The results in Table 4 indicate a statistically significant difference in mean Cape gooseberry productivity between the group of farming families that received crop technologies via digital systems and adopted climate-smart agriculture during crop production and the other three groups of farming families, at the 0.05 level of significance.

However, there was no statistically significant difference in mean Cape gooseberry productivity between the group of farming families who received crop technologies via digital systems during crop production and the group of farming families who adopted climate-smart agriculture and received information on Cape gooseberry husbandry practices from regular extension services during crop production, at the 0.05 level of significance.

At the 0.05 level of significance, there was a statistically significant difference in mean Cape gooseberry productivity between farming families that received crop technologies via digital systems during production and those that received information on crop husbandry practices through regular extension services. Similarly, at the 0.05 level of significance, a statistically significant difference was found between farming families that incorporated

climate-smart agriculture into crop production and those that relied on regular extension services for information on crop husbandry practices.

Conclusion and Recommendation

The study found that Cape gooseberry productivity, measured in kilogrammes per acre, improved when crop technologies were disseminated to farming families through digital systems. Productivity also increased when farming families incorporated climate-smart agricultural practices into crop production

The study recommends supporting extension staff in Baringo County to integrate digital systems into routine extension services and to introduce farmers in the County to the domestication of Cape gooseberry. Farmers should also be encouraged to adopt climate-smart agricultural practices to increase crop productivity.

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Fabrication and Characterization of Biodegradable Plastic Film from Cassava and Sweet Potato Starch Blend

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Abstract
For decades, Petro-based plastics have found extensive industrial applications and are widely used in everyday life. They are tough, corrosion-resistant, lightweight, and can be moulded into various shapes. However, Petro-based plastics resist natural degradation and produce large amounts of carbon emissions during incineration and disposal. Consequently, they cause environmental contamination and pose a serious threat to environmental health. Starch-based biodegradable plastics offer a promising remedy for these challenges. This study aimed to fabricate a biodegradable plastic from a blend of cassava and sweet potato starch and to determine its physical properties (tensile strength) and biodegradability. The starch was obtained from peeled and finely ground cassava and sweet potatoes. After blending, the starch was gelatinized and plasticized using glycerol. To determine biodegradability, bioplastic strips made from the cassava and sweet potato starch blend were buried in garden and compost soils, and degradation efficiency was evaluated. Tensile strength was determined from the ratio of breaking force to the film's cross-sectional area. The sweet potato starch blend biofilm had a tensile strength of 2.378 MPa, followed by the cassava biofilm at 2.18 MPa; the blend was the lowest at 1.175 MPa. The comparative biodegradability test revealed that the starch blend achieved 100 percent degradability in compost soil and 61.53 percent in garden soil, making it the most biodegradable. These findings indicate that the starch-based bioplastic film synthesized from cassava and sweet potato blends demonstrated the greatest biodegradability and material strength. The blend exhibited the highest biodegradability, particularly in compost soil, indicating strong environmental compatibility. These findings highlight the potential of locally available starch-rich crops as sustainable raw materials for producing eco-friendly alternatives to petroleum-based plastics.

Keywords: Biodegradable, bioplastics, plasticizer, starch blend, tensile strength

Introduction

Global reliance on synthetic plastics derived from fossil fuels has created environmental challenges because they resist natural degradation and generate substantial carbon emissions during disposal (Mohanan et al., 2020). While these synthetic plastics are economically beneficial and have diverse applications, they contribute to significant pollution across all environmental compartments, including terrestrial, marine, and atmospheric environments, posing long-term environmental risks (Epps III et al., 2021). Consequently, scientific research has increasingly focused on developing eco-friendly, sustainable, and biodegradable bioplastics derived from renewable feedstocks, with a major emphasis on starch-based polymeric materials (Anugrahwidya et al., 2021).

Currently, global plastic production is estimated at 367 million tonnes annually, with bioplastics accounting for about 1 percent of the total (Rao et al., 2022). The remainder consists of Petro-based plastics. As of 2021, despite this low production, demand for bioplastics is

growing rapidly because of their diverse applications in agriculture, consumer goods, textiles, and packaging (Shafqat et al., 2021). Within the total bioplastics market, the packaging sector accounts for the largest share at 48 percent (Anugrahwidya et al., 2021).

In recent years, the utilization of starch has expanded beyond its traditional applications as an energy source in the human diet, a sizer in the textile industry, and a binder in paper manufacturing. It is now increasingly applied in the development of degradable bio-based bioplastics as a promising substitute for fossil-based plastics (Özdamar & Ateş, 2018). In addition to its biodegradability, starch is widely used in bioplastic development due to its renewability, abundance, and low oxygen permeability (Zoungranan et al., 2020). However, a major drawback frequently reported in its application as a bioplastic material is its high water sensitivity (Rao et al., 2022).

The literature reports numerous studies on the fabrication of bioplastic materials using various crops as starch sources. Özdamar and Ates (2018) reported that bioplastic derived from tapioca starch, extracted from the cassava plant (*Manihot esculenta*), was smooth, flexible, and strong. Nasir and Othman developed a corn-based bioplastic suitable for use as seedling bags. Their study reported that seedling bags made from corn-based bioplastic offer several advantages, including natural decomposition, nutrient supply to young plants, and the elimination of the need for transplanting during planting due to the bioplastic's natural degradability (Nasir & Othman, 2021). Transparent and low deformation strength albumen/starch based bioplastic have been developed (Gonzalez-Gutierrez et al., 2010). However, the literature provides limited information on developing bioplastics from starch blends. Although some reviews have discussed current developments and trends in the use of starch blends to produce bioplastics with improved mechanical and degradability properties, the available data remain insufficient (Jayarathna et al., 2022).

Starch-based polymers, particularly those developed from abundant crops such as cassava and sweet potato, have distinct advantages. They are naturally biodegradable and carbon-neutral, and their cultivation can also support agricultural economies in developing countries. This study examines the mechanical and degradability benefits of blending these two starches, critically assessing how starch blends may improve both film-forming capabilities and environmental degradation performance when compared to individual starch systems.

Starch is an abundant and biodegradable polysaccharide that has become a promising raw material for the development of bioplastics due to its cost-effectiveness, ability to form thermoplastic films, and its natural availability (do Val Siqueira et al., 2021). Among available starch sources, cassava (*Manihot esculenta*) and sweet potato (*Ipomoea batatas*) have emerged as technologically viable candidates, owing to their high amylose content, cultivation feasibility, and demonstrated thermoplastic behaviour when plasticized (Gadhave et al., 2018). Blending these starches shows particular promise in bridging the mechanical-durability versus biodegradability gap that often limits bioplastic applications.

This investigation explored the fabrication of bioplastic films using a 1:1 (w/w) blend of cassava and sweet potato starch, modified with a glycerol-acetic acid plasticizer system. The mechanical properties of the starch-based biofilm were evaluated through tensile strength testing. Biodegradability was quantified via mass loss measurements in both controlled compost and garden soil under ambient laboratory conditions over 12 weeks. This garden soil setup models the natural soil environment while controlling fluctuating environmental factors.

Tensile strength and biodegradation performance parameters were selected to concurrently assess practical material usability and environmental compatibility—a critical parameter for sustainable material development. This work defined mechanical properties (tensile strength) and biodegradation efficiency as the dependent variables. The starch blend composition ratio was treated as the independent variable. To ensure consistency and validity, several variables were kept constant. These controlled variables included total starch mass per

film, glycerol concentration (maintained at 30% w/w of dry starch), drying temperature, casting volume, and gelatinization conditions.

This work therefore aims to develop a viable alternative to conventional plastics by systematically evaluating a 1:1 w/w blend of cassava and sweet potato starch. The central objective is to determine whether this novel material can achieve a crucial balance: possessing the mechanical performance necessary for practical use while maintaining rapid and complete biodegradability**,** thereby offering a solution to plastic pollution through indigenous bioresources.

Materials and Methods

Bioplastic Film Fabrication Procedure

Fresh cassava roots (*Manihot esculenta*) and sweet potato (*Ipomoea batatas*) were used as starch sources. Root processing involved washing, peeling, and drying within 24 hours of harvest. Analytical grade glycerol (≥99.5% purity, Sigma-Aldrich) and deionized water were used in the plasticizer formulation. A 1:1 (w/w) blend of 10 g each of sun-dried and ground cassava and sweet potato was used for film fabrication. To the starch mixture, a 100 mL of distilled water was added and stirred until the starch completely dissolved.

This blend was modified using a glycerol-acetic acid plasticizer system formulated from a 10 mL of 30 percent glycerol and 6 mL of 5 percent acetic acid, with rapid stirring to prevent starch hydrolysis (do Val Siqueira et al., 2021). The mixture was subsequently heated on a hot plate while continuously stirring and maintaining the temperature between 75 °C and 95 °C (Fluke 62 MAX IR thermometer) until the solution turned translucent (Jayarathna et al., 2022). The gel was evenly spread on a 0.03 mm sheet of aluminium foil and left to cool and dry at ambient laboratory temperature for 48 hours.

The constant weight method was used to confirm the film's dryness, with the film weighed every 6-12 hours until the % mass change was < 1%. After drying, the bioplastic film was carefully peeled from the mould and tested for tensile strength and biodegradability. Control films were also prepared from pure cassava and pure sweet potato starch using the same procedure, maintaining a constant total starch mass of 20 g in each case.

Biodegradability Test

Biodegradation studies were conducted according to the method proposed by Kundu and Payal (2022), in which pre-weighed film samples were buried in soil and percent mass loss was determined after a given incubation period. Biodegradability tests were done using compost soil (pH 7.2 ± 0.3, C/N ratio 25:1) and garden soil (sandy loam, 2.1% organic content) at 28 °C**.** The bioplastic films were weighed and subsequently buried in 2-liter polypropylene containers holding 1.5 kg of growing material. Each medium (garden soil and compost) was replicated three times. The film samples were buried to a depth of 5 cm. The containers were clearly labelled with the sample type and its original mass before burial.

Moisture level was maintained at 60 percent for garden soils and 50 percent for compost by periodically adding 15 mL and 10 mL of distilled water, respectively. The containers were left at room temperature in the laboratory for seven days. Subsequently, the samples were removed, cleaned of any remaining soil particles, and weighed again (Kundu & Payal, 2022). The degradation efficiency, expressed as percentage weight loss, was calculated using the conventional formula in Equation 1, following Nandiyanto et al. (2020). The equation ignores the correction factor for the soil adsorption component (Nandiyanto et al., 2020).

$$Biodegradation\ (\%) = \frac{(W_i - W_f)}{W_i} \times 100 \qquad (1)$$

Where, W_i = Initial mass of biofilm, W_f = Final mass of biofilm after degradation.

The samples were carefully removed from the soil after the incubation period, gently cleaned to remove any remaining soil particles, and then oven-dried at 50 °C to a constant weight before the final mass (W_f) was determined (Kundu & Payal, 2022). This ensured that changes in moisture content did not affect mass loss, except for polymer loss due to biodegradation.

Tensile Strength Test

Tensile strength of biofilm was evaluated following the method proposed by Gabriel et al. (2021). This method calculates tensile strength as the force at break divided by the strip's cross-sectional area, expressed in megapascals (MPa). Bioplastic strips measuring 0.5 cm by 4 cm were cut from defect-free sections of the films for testing. The micrometre screw gauge was used to measure the thickness of the bioplastic strip before stretching. This was done in three replicates to ensure uniform thickness by averaging the measurements. Tensile testing was executed by stretching clamped samples at a steady rate of 10 mm/min until they broke. The force required to cause this break (F_{max}) was measured using a spring scale, zeroed to account for the clip mass (Gabriel et al., 2021).

The obtained measurements were used to compute the cross-sectional area. Force at break (F_{max}) was converted to MPa using Equation 2, a conventional equation for determining tensile strength of starch-based biofilms (Safitri et al., 2022). Tests were considered invalid if breaking occurred within 3 mm of the clamps.

$$Tensile\ strength\ (\sigma) = \frac{F_{max}}{A} \times 10^{-6} \quad (2)$$

Results and Discussion

Biodegradability Test Analysis

Biodegradation testing in this investigation showed that the soil environment (compost versus garden soil) and starch source strongly influence the biodegradability of starch-based bioplastic films, as shown in Table 1. The bioplastic film developed from the starch blend degraded completely in compost, with no recovery from the initial 1.26 g, demonstrating exceptional biodegradability. In garden soil, degradation was moderate, with 1.07 g recovered from 1.61 g; this may be due to high microbial activity in compost, which enhances biodegradability.

Table 1: Degradability of Bioplastic Films from Cassava, Sweet Potato and Starch Blend

Bioplastic Type	Burial Material	Mass Before Burial (g)	Mass After Burial (g)
Starch Blend	Compost	1.26	0.00
Starch Blend	Garden Soil	1.61	1.07
Cassava Starch	Compost	2.25	1.56
Cassava Starch	Garden Soil	2.23	2.44 (wet)
Sweet Potato Starch	Compost	0.60	0.18
Sweet Potato Starch	Garden Soil	0.26	0.10

The bioplastic film developed from the starch blend degraded completely in compost, with no recovery from the initial 1.26 g, demonstrating exceptional biodegradability. In garden soil, the degradation was moderate, with 1.07 g recovered from 1.61 g. This mass loss is attributed to high microbial activity in compost, which enhances degradability. The cassava starch-based bioplastic degraded partially in compost, decreasing from 2.25 g to 1.56 g, but in garden soil, the mass increased slightly from 2.23 g to 2.44 g. This mass gain may reflect

moisture absorption, suggesting that cassava starch-based films are hygroscopic and unstable in humid settings, as observed in related work by Zoungranan et al. (2020).

Although our work associated the variability in degradability with the starch source, related studies have also linked degradability efficiency to the glycerol or plasticizer content, as these enhance flexibility and hygroscopicity, thereby facilitating microbial-assisted degradation (Gurunathan et al., 2025). Existing literature informed the choice of glycerol levels used in this study. Concentrations of glycerol in the range of 20–40% w/w relative to starch mass enhance flexibility while reducing brittleness of starch-derived bioplastic films (Saberi et al., 2016; Zoungranan et al., 2020).

Cassava is rich in amylopectin, which is essential for the flexibility and transparency of the bioplastic film (Chaffa et al., 2024). Sweet potato contains a higher amylose content, a material that enhances the strength and stability of the film (Wahyanti et al., 2023). A 1:1 w/w starch blend was chosen because it provides a balance of these features. Moreover, previous studies have demonstrated that this balanced ratio improves mechanical, functional, and barrier properties (Jayarathna et al., 2022).

The mass in compost decreased from 0.60 g to 0.18 g, and in garden soil from 0.26 g to 0.10 g. Bioplastics degraded more extensively in compost than in garden soil, directly linking the biodegradation process to soil conditions such as microbial density and organic content.

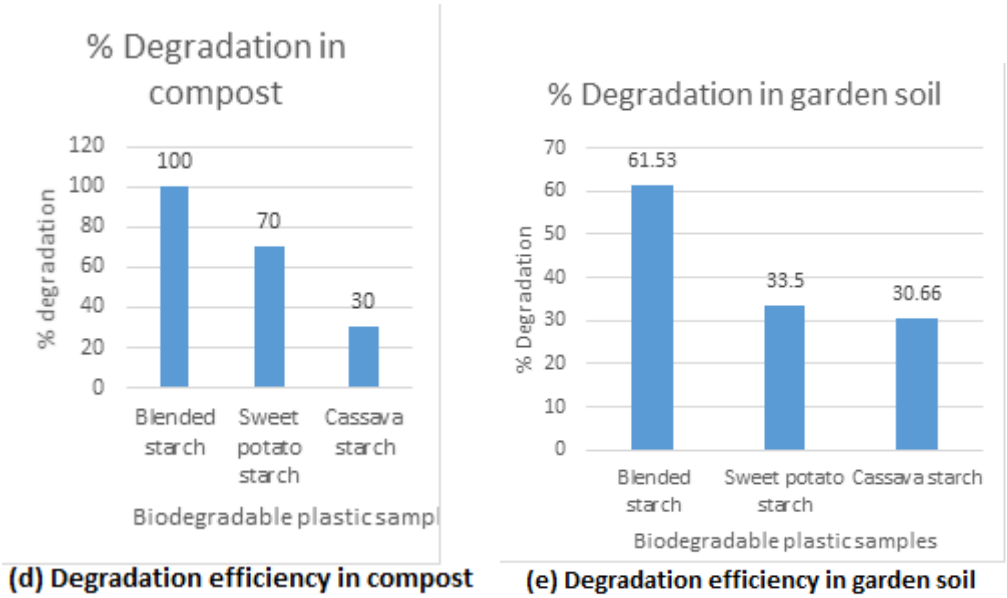
Figure 1 below shows images (a), (b), and (c) of bioplastic films fabricated from starch blends, cassava and sweet potato, respectively. The biofilms are transparent, smooth, and have a continuous surface. These properties are associated with well-gelatinized starch during film formation. During film development, moisture content was maintained at 10–15 percent to allow proper gelatinization of starch (Shah et al., 2017).



Fig. 1: Images of Developed Bioplastic Films from Starch Blend, Cassava and Sweet Potato

Figure 2 shows the biodegradation efficiency findings. Notable observations include 100 percent degradation efficiency of the starch blend in compost, as shown in Figure 2(d), and a decent 61.53 percent efficiency in garden soil, displayed in Figure 2(e). This can be associated with the synergistic effect of the starch blend; possibly, blending modified the polymer network by increasing the porosity of the amorphous structure, thereby enhancing accessibility to microbial enzymes (Thakur et al., 2018). Additionally, blended starch could have higher water

absorption or increased hygroscopicity, increasing water retention and microbial activity (Mohanan et al., 2020).



(d) Degradation efficiency in compost (e) Degradation efficiency in garden soil

Fig. 2: **Degradation Efficiency of Starch Sources in Compost and Garden Soil**

Sweet potato starch degradation efficiency was 70 percent in compost and 33.5 percent in garden soil. Cassava starch showed the lowest % degradability in both compost and garden soils. This is likely due to higher amylopectin content, which creates a branched molecular structure that limits access by microbial enzymes. Consequently, the rate of enzymatic hydrolysis is reduced during composting or soil burial.

Tensile Strength Testing

The tensile strength of the developed bioplastic varied according to the starch source from which it was derived, as shown in Table 2.

Table 2: Tensile Strengths of Starch from Various Sources

Sample type	Average Thickness (10^{-4}m)	Tensile strength (Mpa)
Cassava and sweet potato blend	3.5	1.175
Sweet potato	2.9	2.378
Cassava	2.5	2.18

The sweet potato starch-based bioplastic had the highest average tensile strength (2.378 MPa), despite its lower average thickness (2.9×10^{-4} m). This shows that sweet potato starch may contain a higher amylose-amylopectin content, which forms stronger hydrogen bonds during gelatinization (Lee & Yeo, 2021).

The tensile strength of the fabricated bioplastic film was assessed as the dependent variable. The plasticizer (glycerol) amount and the starch blend composition were the independent variables. Film thickness, gauge length, drying temperature, and the bioplastic film fabrication method served as controlled variables.

The cassava starch-based bioplastic had a tensile strength of 2.18 MPa and a thickness of 2.5×10^{-4} m, indicating good mechanical strength, but relatively lower than that of the sweet potato counterpart. The blended starch bioplastic had the lowest tensile strength (1.175 MPa)

despite having the highest thickness (3.5×10^{-4} m). The blended bioplastic also has the lowest mechanical durability, limiting its use in rigid packaging materials.

These findings suggest that bioplastics generated from specific starch sources (cassava and sweet potato) are mechanically stronger than blended formulations and may, therefore, be more suitable for applications requiring greater mechanical durability and tensile resistance (Ismail et al., 2016). The relatively high degradability of sweet potato starch, combined with its robust tensile properties, suggests that it offers the dual advantage of strength and biodegradability. As observed by Boey and his group, such materials are suitable for packaging materials used in extreme conditions (Boey et al., 2022). The higher mechanical properties and its film-forming abilities are also attributable to its granular structure and low lipid-protein traces in sweet potato starch (Song & Zheng, 2008). As a result, the sweet potato film demonstrates superior load-bearing capacity. The lower tensile strength of the starch-blend bioplastic indicates its potential use in low-density packaging materials.

This study, however, did not investigate the influence of the plasticizer system or the v/v ratio of the plasticizer on the mechanical stability, structural, and environmental properties of the resulting bioplastic film.

Conclusion

This study examined the potential of starch-based bioplastics as alternatives to Petro-based, conventional synthetic polymers by evaluating their biodegradability and tensile strength. The bioplastic strips developed from cassava, sweet potato, and blend starches showed variability in biodegradability and mechanical strength. Bioplastic made from the starch blend showed 100 percent degradation efficiency in compost and a notable 61.53 percent in garden soil. However, its tensile strength (1.175 MPa) was the lowest. Sweet potato starch, under similar soil conditions, showed a 70 percent degradation efficiency in compost and 33.5 percent in garden soil, while exhibiting the highest tensile strength of 2.378 MPa. This bioplastic is suitable for rigid packaging applications. Cassava starch bioplastic showed the lowest degradability in both compost and garden soil, but with a moderate tensile strength—higher than that of the starch blend —due to its higher amylopectin content, which creates a branched structure that limits access by microbial enzymes.

This study has demonstrated that the biodegradability and mechanical properties of starch-based bioplastics are primarily influenced by the starch source and blend. To build on these findings, future work should investigate additional factors, such as composite materials, protein-starch combinations, soil microbial composition, and the concentration and type of plasticizer used.

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Synthesis and Application of Zinc Oxide Nanoparticles as Efficient Photocatalysts for Organic Pollutant Degradation: Bromothymol Blue as a Model System

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Abstract
The release of synthetic dyes and organic contaminants into water bodies from industrial effluents poses significant environmental threats. Photocatalysis using semiconductor nanoparticles, such as zinc oxide (ZnO), offers a sustainable solution due to its high photocatalytic activity and eco-friendliness. This study examined the synthesis of ZnO nanoparticles via a chemical precipitation reaction using zinc nitrate and sodium hydroxide at 80°C. It further evaluated their photocatalytic efficiency in degrading bromothymol blue (BTB) as a model organic pollutant. BTB's degradation was monitored by measuring absorbance at 616 nm, corresponding to its deprotonated form (pH ~7.6). A linear decrease in absorbance over time was reported (R^2 = 0.9997), indicating efficient degradation, with ANOVA confirming statistical significance (R^2 = 0.9996, SE = 0.310). These findings highlight the efficiency of ZnO nanoparticles in photocatalytically degrading BTB under UV light irradiation, affirming their potential application in wastewater treatment. This efficiency is likely due to the generation of reactive oxygen species by ZnO under visible light. Notably, the ZnO nanoparticles exhibited superior performance compared to TiO_2 under identical conditions, as documented in previous related studies. While these results highlight ZnO's potential for wastewater treatment, future studies should characterize the nanoparticles to correlate structure with activity. Overall, this study demonstrates the promising application of ZnO nanoparticles as an effective, cost-effective, and reliable photocatalytic solution for degrading organic pollutants in environmental cleanup processes.

Keywords: Bromothymol blue, photocatalysis, organic contaminants, wastewater, ZnO nanoparticles

Introduction

Water pollution caused by synthetic dyes has become a serious environmental concern as they are widely used in the manufacture of textiles, paper, plastics, and medicines (Yusuf, 2019). These dyes are predominantly chemically stable, resistant to natural degradation, and represent significant health and environmental concerns when introduced into aquatic systems (Chavan, 2013). Conventional treatment methods, such as coagulation, filtration, and chemical oxidation, often fail to adequately eliminate persistent dye pollution, emphasizing the need for more advanced and long-term remediation strategies (Slama et al., 2021).

Global industrial, scientific, and technological advancements have led to a growing demand for new chemicals in industrial production activities (Vasanthi et al., 2024). Organic dyes are among the newly developed compounds of significant industrial importance, particularly in the paper, textile, cosmetics, and food processing industries. However, studies on surfaces and wastewater have reported these dyes as potentially toxic (Danwittayakul et al., 2015). Consequently, effective degradation strategies for these pollutants have garnered global

attention. Moreover, dyes and their associated intermediates can undergo reductive transformations, forming carcinogenic compounds that pose serious risks to humans, microorganisms, and aquatic ecosystems (Vasanthi et al., 2024). This underscores the urgent need to remove them from environmental compartments and matrices.

Among other new approaches, photocatalysis employing semiconductor nanoparticles stands out as a particularly promising method for addressing environmental pollutants (Albarakaty et al., 2023). Notably, zinc oxide (ZnO) nanoparticles have drawn interest due to their high photocatalytic activity, low cost, and UV-resistant photochemistry (Chemingui et al., 2024). Although the ability of ZnO to degrade organic dyes has been extensively studied, focused tests against specific contaminants, such as bromothymol blue (BTB), remain useful for improving wastewater treatment techniques.

ZnO is unique among metal oxides because of its wide band gap, strong oxidative properties, and capacity to create reactive oxygen species under illumination, which can degrade complicated dye molecules into less damaging byproducts (Albarakaty et al., 2023). The photocatalytic efficacy of ZnO is heavily impacted by parameters such as particle size, shape, crystallinity, and surface area, all of which are controlled by the synthesis procedure. Sol-gel, hydrothermal, and chemical precipitation techniques have allowed for control of these properties (Uribe-López et al., 2021) with the chemical precipitation method being used in this investigation. Tailoring synthesis conditions remains critical to improving ZnO performance in environmental applications (Chemingui et al., 2024).

This study examines the photocatalytic breakdown of bromothymol blue, a model organic pollutant widely used in laboratories and industries. The study uses ZnO nanoparticles under UV radiation to analyse the dye's degradation and discoloration behaviour under controlled laboratory conditions, but does not include kinetic analysis or morphological characterization, which were extensively evaluated elsewhere in related studies (Arora et al., 2014; Salim et al., 2022). The goal is to demonstrate ZnO's practical effectiveness in pollutant breakdown and contribute to environmental remediation. Despite the lack of extensive material characterization, the findings support the viability of ZnO-based photocatalysis for long-term water treatment solutions. Figure 1 shows the schematic structure of bromothymol blue.

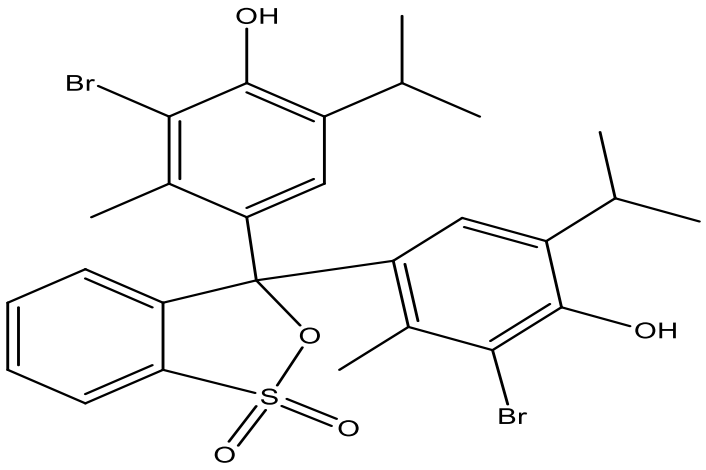


Fig. 1: Chemical Structure of Bromothymol Blue

Materials and Methods

Materials and Experimental Procedure

Zinc nitrate hexahydrate ($Zn(NO_3)_2.6H_2O$), sodium hydroxide, and bromothymol blue used in this investigation were purchased from reputable suppliers and were of high purity (> 99 %). A 10-ppm solution of bromothymol blue was prepared by dissolving 10 mg of the indicator in distilled water, corresponding to 10 mg/L of solution. Zinc oxide nanoparticles were fabricated

by the precipitation method. A 0.1 M solution of zinc nitrate hexahydrate, used as the ZnO precursor, was prepared by dissolving the appropriate mass in deionized water, as described by Ghorbani and his group (Ghorbani et al., 2015). The solution was heated to approximately 60 °C with continuous stirring. A 0.2 M sodium hydroxide solution, serving as the precipitating agent, was added dropwise under constant stirring until the pH reached 8, allowing the precipitation of $Zn(OH)_2$.

To ensure complete reaction, the mixture was stirred for an additional 2 hours. To remove residual ions, the precipitate was allowed to settle, then repeatedly rinsed with distilled water and ethanol. The rinsed precipitate was subsequently dried overnight at 80°C. The obtained powder was then calcined in a muffle furnace at 400°C for 2 hours to produce crystalline ZnO nanoparticles.

Evaluation of Photocatalytic Performance

The photocatalytic performance of the synthesized ZnO nanoparticles was assessed by measuring bromothymol blue degradation under UV irradiation. A mixture of 100 mL of BTB solution and 0.05 g of ZnO nanoparticles in a 250 mL conical flask was magnetically stirred for 30 minutes in the dark to achieve adsorption-desorption equilibrium (Uribe-López et al., 2021). The resulting suspension was then subjected to UV radiation using a mercury vapor lamp (365 nm) while constantly swirling. After every 15 minutes, 5 mL aliquots were removed and centrifuged to remove ZnO particles. The absorbance of the clear solution was then measured using a UV-Vis spectrophotometer at 616 nm, λ_{max} for bromothymol blue.

The degradation efficiency (% degradation) was computed using Equation1, based on the change in absorbance values over time. The extent of dye degradation was assessed from the relative decrease in absorbance. All experiments were carried out in triplicate, and the values were averaged. Characterization, kinetic modelling and adsorption studies were not considered in this work.

$$\%\ Degredation = \left(\frac{A_0 - A_t}{A_0}\right) \times 100 \quad (1)$$

Where A_0 denotes the absorbance at t = 0, and A_t the absorbance at a given time t

Results and Discussion

The photocatalytic activity of the ZnO nanoparticles was evaluated by monitoring changes in absorbance of the dye solution over time, corresponding to the contact duration between the nanoparticles and the model contaminant. A consistent decrease in absorbance with longer contact time indicated a corresponding decrease in bromothymol blue concentration, confirming successful degradation under UV illumination. The photodegradation process involves the breakdown of BTB's chromophoric structure (Mehta et al., 2021). Table 1 displays the changes in the absorbance of BTB with increasing contact time with ZnO NP and the corresponding % degradation.

Table 1: **% Degradation and Change in Absorbance with Increase in Contact Time**

Time (min)	0	15	30	45	60	75
Absorbance(nm)	1.98	1.79	1.58	1.37	1.18	0.97
% Degradation	0.0	10.4	20.0	30.8	40.4	51.0

The data show the trend of change in the absorbance of the model organic pollutant solution over time. This change occurred as photodegradation and discoloration took place in the presence of ZnO nanoparticles. The decreasing absorbance trend with increasing contact time with ZnO nanoparticles suggests a highly effective photocatalytic-driven activity of the nanomaterial. The attractive photocatalytic performance is linked to their large surface area

and strong oxidative capabilities. According to Zhang et al. (2021), these features facilitate the generation of reactive oxygen species (ROS) under ultraviolet (UV) light exposure. The mechanism involves the absorption of UV light by ZnO, which excites electrons from the valence band to the conduction band, leaving behind holes in the valence band, as discussed under the photocatalytic degradation mechanism below.

The initial concentration of bromothymol blue solution was indicated by an absorbance of 1.98 at t = 0, and a gradual decrease in concentration was observed throughout the 75-minute contact time with the nano-ZnO. The substantial ~51 percent degradation confirms that ZnO nanoparticles enhance photocatalytic reaction processes, consistent with findings from previous studies on ZnO-based photocatalysts (Bhandari et al., 2023). Further research could delve into how mixed metal doping or joint semiconductor implementation with ZnO materials will optimize visible light performance (Zhang et al., 2021).

Figure 2 illustrates the variation in percentage degradation of bromothymol blue by ZnO nanoparticles with time under UV irradiation. The degradation increased steadily over time, with a strong linear correlation ($R^2 = 0.9997$) described by the equation $y = 0.6773x + 0.04$. This linear trend suggests a zero-order or pseudo-first-order kinetic behaviour, consistent with findings by Mehta et al. (2021). ZnO nanoparticles achieved 10.4 percent degradation at 15 minutes and 51 percent at 75 minutes, indicating high photocatalytic efficiency. Future studies could evaluate the potential influence of enhanced particle size, surface properties, and improved visible light responsiveness on the photodegradation efficiency of nano-ZnO.

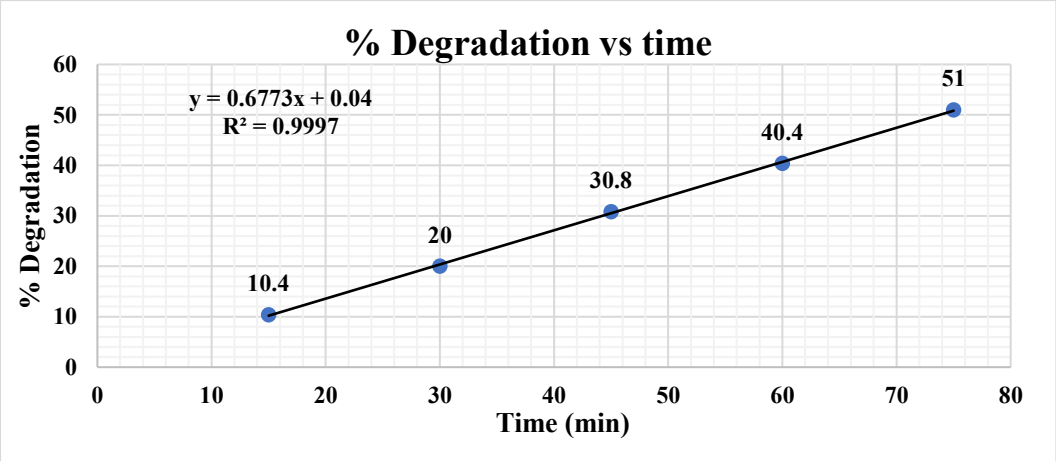


Fig. 2: % Degradation of BTB Over Contact Time with ZnO Nanoparticles

Evidently, there is a linear relationship between percentage degradation and contact time, with an R^2 value of 0.9997 indicating a strong correlation between the variables.

An analysis of variance (ANOVA) was used to assess the effect of contact time on bromothymol blue (BTB) degradation by ZnO nanoparticles. The ANOVA table illustrates variability in observed degradation percentages over time and indicates whether the changes in degradation are statistically significant. The F-statistic and p-value indicate the effect of contact time on the photocatalytic effectiveness of ZnO nanoparticles. The ANOVA results assume normal distribution of residuals. Table 2 summarizes the statistical findings based on this assumption.

Table 2: ANOVA Summary Table

	df	SS	MS	F	Significance F
Regression	1	1065.024	1065.024	11094	1.887×10^{-6}
Residual	2	0.288	0.096		
Total	3	1065.312			

Legend: df-Degrees of freedom, **SS** Sum of squares, **MS** Mean squares, **F** is F-factor

Regression analysis was used to investigate the relationship between contact time and percentage degradation of bromothymol blue (BTB) by ZnO nanoparticles. Significant statistical indicators such as the correlation coefficient and coefficient of determination were used to assess the strength of the linear relationship between these variables. These indicators show how well the contact period predicts the extent of photocatalytic degradation.

Table 3: Regression Statistics Table

Multiple R	0.999864819
R Square	0.999729657
Adjusted R Square	0.999639542
Standard Error	0.309838668
Observations	5

The independent and dependent variables show an extremely powerful link through the Multiple R value of 0.9999, which shows a nearly perfect positive linear correlation. The independent variable successfully explains 99.97 percent of the dependent variable variations since the R^2 value reaches 0.9997. The Adjusted R^2 value of 0.9996 persists at a nearly perfect level even after accounting for adjustment factors and predictor variables, which confirms the model's reliability and accurate data match. The model's precision is clear from the Standard Error of 0.310, as observed values are only 0.31 units apart from predicted values, given the scale of the variables. The research data contains only five observations. Table 4 shows regression coefficients for the correlation between % degradation and contact time.

Table 4: Regression Coefficients for the Relationship Between Contact Time and Percentage Degradation of Bromothymol Blue

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-0.6	0.3249	-1.8464	0.1620	-1.6342	0.4342	-1.6342	0.4342
X Variable 1	0.688	0.006532	105.33	1.887E-06	0.6672	0.7088	0.6672	0.7088

The model includes an intercept value of -0.6, but its p-value (0.162) shows its statistical insignificance at a 5 percent significance level, thus demonstrating minimal influence on the change in the dependent variable. In contrast, Variable 1 Coefficient (0.688) exhibits high significance (p-value = 1.8878E-06), which indicates a 0.688 unit increase in the dependent variable for each unit increase in X Variable 1. The interval between Lower 95% = 0.667 and Upper 95% = 0.709 does not include zero, thus validating its significance.

A normal probability plot, displayed in Figure 3, was generated to determine whether the regression residuals followed a normal distribution. This visual diagnostic aids in assessing the suitability of the linear regression model by correlating the observed residual patterns to those

expected under a normal distribution. The plot shows a near-linear trend, suggesting the residuals are nearly normally distributed.

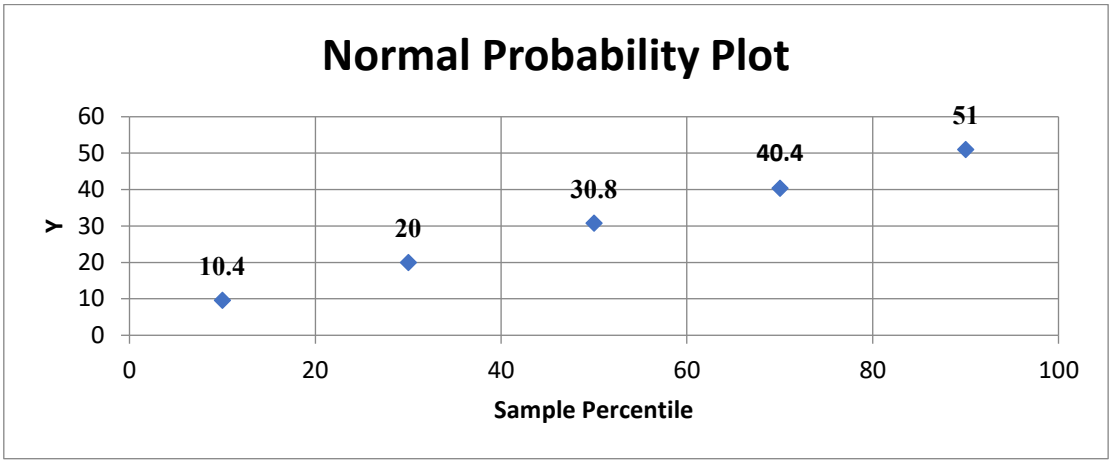


Fig. 3: Normal Probability Plot of % Degradation Data

Photocatalytic Degradation Mechanism of ZnO (Involving •OH and h^+ action)

Photocatalytic dye degradation has been studied worldwide, regardless of a country's level of scientific development. Typical variables considered for degradation research include the type and concentration of the dye, the desired level of degradation, the catalyst used, and the intensity and source of photons used (Singh et al., 2022). In photocatalytic degradation, the pollutants are degraded under UV-visible light irradiation in the presence of catalysts. Due to their susceptibility to UV and visible light radiation, various semiconductor metal oxide nanomaterials, including Fe_2O_3, TiO_2, WO_3, and Cu_2O are used as photocatalysts (Motamedi et al., 2022). ZnO nanoparticles present a huge promise in photocatalytic performance, especially in a variety of applications, including wastewater treatment, environmental pollution reduction, and water splitting for hydrogen production (Ragupathy et al., 2022).

Dye degradation by engineered nanomaterials occurs in the presence of UV light (Singh et al., 2022). The mechanism is a four-step reaction (Tomar et al., 2020): (a) the photocatalyst absorbs light and excites the electrons of the semiconductor photocatalyst to move from the valence band to the conduction band; (b) potential e-/h+ pair recombination as a result of the photogenerated electrons and holes' low stability; (c) generation of active species (radicals) on the surface due to the trapping of electron-hole pairs initiates redox reactions; and (d) finally, pollutant degradation occurs, as depicted in Figure 3.

The photocatalytic properties of nanomaterials result from the formation of an excited electron/hole pair when the material is subjected to UV light (Tomar et al., 2020). UV radiation causes charge separation by exciting an electron (e-) from the valence band to the conduction band of the nanomaterial, generating a hole (h+, a region of positive charge density) in the valence band.

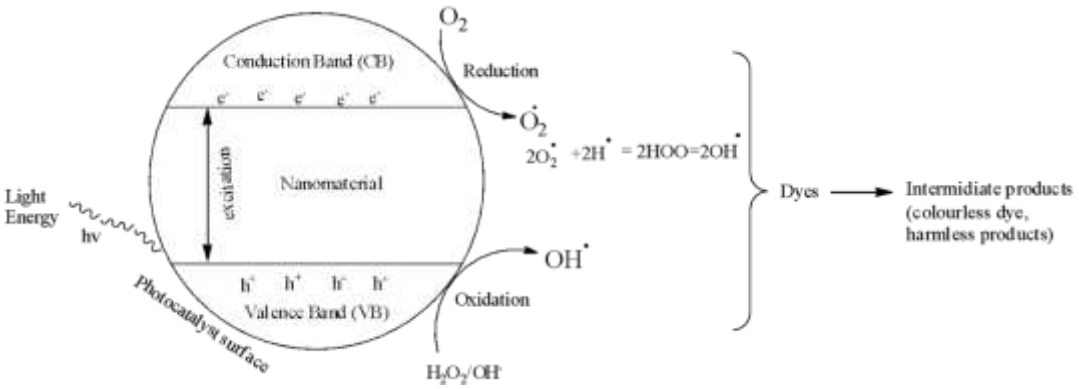


Fig. 4: Photocatalytic Degradation Phenomenon of Nanomaterials

As illustrated in Figure 4, the photocatalytic process generates two species: a photoexcited electron and a hole, represented in Equation 2

$$TiO_2 + h\upsilon \rightarrow e^- + h^+ \quad (2)$$

Redox reactions of photogenerated electron-hole pairs may produce oxidant radical species such as superoxide (O_{2^-}), hydroxyl ($OH^{\cdot}$), or peroxide ($OOH^{\cdot}$) (Jeyaraj et al., 2021). On the nanomaterial surface, these radical species produce heterogeneous photodegradation of organic substrates such as dyes (Anjali et al., 2022). The very presence of the hydroxyl radical, which is a highly strong oxidizing agent, causes the majority of these degradation processes (Tomar et al., 2020) as depicted in Equation 2.

$$\text{Dye} + OH^{\cdot} \rightarrow \text{Degradation products} \quad (3)$$

As described in Equations 4 and 5, dyes that do not react with the hydroxyl radical can proceed via either the oxidation or reduction route (Jeyaraj et al., 2021).

$$\text{Dye} + {h_{VB}}^+ \rightarrow \text{Degradation products} \quad (4)$$

$$\text{Dye} + {e_{CB}}^- \rightarrow \text{Degradation products} \quad (5)$$

Conclusion

This study demonstrated that ZnO nanoparticles have effective photocatalytic activity for photodegrading bromothymol blue dye under UV radiation. Within 75 minutes, a degradation efficiency of approximately 51 percent was achieved, with a strong linear relationship between contact time and % degradation. Statistical analyses, including regression and ANOVA, confirmed the data's significance and reliability, and the normal probability plot validated the normality assumption. The efficiency of nano-ZnO is attributable to its large surface area and capacity to produce reactive oxygen species upon UV activation. These findings suggest ZnO nanoparticles' potential as low-cost, environmentally friendly photocatalysts for dye removal in wastewater. Future investigations could examine how particle size, surface properties, and doping affect visible-light absorption and the photocatalytic efficiency of nano-ZnO.

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Influence of Artificial Intelligence on The Efficiency and Accuracy of Credit Scoring in Digital Lending in Kenya

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Abstract
Kenya's financial services sector has rapidly evolved, with digital lending playing a crucial role in fostering economic growth and financial inclusion. However, despite the ease of access to financing through digital lending, the sector has faced many challenges, including rising default rates, unorthodox loan collection methods, limited borrower information to minimize *repayment risks*, *credit risk*, *fraud*, and *operational inefficiencies*. Drawing on Diffusion of Innovation (DoI) theory, this study examines how artificial intelligence affects the efficiency and accuracy of credit scoring in digital lending in Kenya. Specifically, it will assess the accuracy and effectiveness of AI in credit scoring, its efficiency in processing credit/loans, and its role in improving customer and institutional outcomes. Using a descriptive research design, a mixed-methods approach incorporating structured surveys and interviews will gather data from Kenya's 32 regulated digital lenders. The data will cover the period from when each firm adopted AI technology up to 2025. The study will test validity and reliability using content validity and Cronbach's alpha. This study aims to provide insights into how AI-powered digital lending can be leveraged to reach and include the unbanked population. Similarly, the solutions generated aim to maximize AI's effectiveness and relevance within Kenya's socio-economic and cultural context.

Keywords: Artificial intelligence, credit scoring, digital lending, efficiency, effectiveness

Introduction

Kenya's financial services sector has evolved rapidly, with digital lending playing a crucial role in fostering economic growth and financial inclusion. This exercise began in 2012, after Safaricom launched M-Shwari. Since then, the number of digital lenders and loans disbursed has grown substantially. By October 2023, the Central Bank of Kenya (CBK) had regulated 32 digital lenders, yet about 400 applications were seeking regulation (KIPPRA, 2023).

However, despite the ease of access to financing through digital lending, the sector has faced many challenges, including increased default rates resulting in negative listings by the Credit Reference Bureau (CRB), aggressive collection of loans using unorthodox means (KIPPRA, 2023), and limited information about the borrower's characteristics to minimize repayment risks, credit risk, fraud, and operational inefficiencies (FSD, 2019).

Defined as the simulation of human intelligence processes by machines, especially computer systems (Laskowski, 2023), Artificial Intelligence (AI) refers to the science of making machines that can think like humans while processing substantial amounts of data in diverse ways, unlike humans. AI includes machine learning (ML), AI-powered automation tools, and natural language processing (NLP) (Lopez, 2024). The goal of including them in any process is to help them recognize patterns, make decisions, and judge like humans (Pattam, 2021).

Given the challenges facing digital lenders, Addy et al. (2024) observed that AI in credit scoring offers significant benefits for financial inclusion and risk management. However, they also emphasize the need to address ethical concerns and potential biases. As such, they recommend further research into the long-term impacts of AI in credit scoring, the scalability of AI models, and their applicability across various financial contexts. Building on these insights, this study aims to examine the role of AI in credit scoring, with a focus on its accuracy and efficiency in the digital lending sector in Kenya.

Caire and Kossman (2003) defined credit scoring as a scientific method of assessing the credit risk associated with new credit applications. Regarding the efficiency and accuracy of credit scoring in digital lending, AI has been used to analyse past (historical) clients' and business data to identify trends, better understand (potential) clients, and predict future events such as credit repayment (Vidal & Barbon, 2019). This efficiency describes minimizing material inputs to maximize economic outputs (van Ewijk, 2018). Therefore, once AI is adopted for efficiency purposes, businesses benefit from cost savings; the ability to identify and capitalize on new opportunities improves; better customer-focused service; quick processing of many applications, minimizing the costs associated with manual credit evaluation and optimizing resource utilization in order to obtain better overall performance and reduced wastages (Vidal & Barbon, 2019). However, accuracy refers to the ability to correctly predict a borrower's likelihood of repaying a loan. When used appropriately, the credit scoring system then classifies borrowers as either low-risk or high-risk based on their creditworthiness (Caire & Kossman, 2003).

As observed by De Cnudde et al. (2019), credit score information comes from socio-demographic data on gender, age, civil status, business experience, time at the current residence, and type of residence; the number of days a client is delinquent; personal credit history with other financial institutions or utility companies; psychometric data, which assesses a person's knowledge, abilities, attitudes, and personality traits; and big data, which includes information from phone companies, utilities, retailers, or social networks (Facebook, Twitter, LinkedIn, Yahoo!).

Accordingly, this paper examined how Artificial Intelligence influences the efficiency and accuracy of credit scoring in Kenya's digital lending sector. Specifically, it assessed credit scoring accuracy, AI effectiveness, efficiency in processing credit and loans, and its role in improving customer and institutional outcomes.

This study adopted the Diffusion of Innovation (DoI) Theory introduced by Rogers and Williams (1983). However, the theory was significantly updated in 2003. This theory explains how new ideas and technologies spread within society. It highlights five factors that influence why people or organizations adopt innovations. These factors include: its benefits, how well it fits with existing practices, how easy it is to use, whether it can be tested, and how visible its results are. The theory also describes five stages that people go through in deciding to adopt something new. These stages are: learning about it, being persuaded, making a decision, putting it into use, and confirming that choice. Researchers have applied this theory in agriculture, marketing, public health, and technology. This study focuses on technology implementation, specifically on how AI-driven solutions like machine learning affect credit scoring and fraud detection within Kenya's digital lending sector, where trust and familiarity remain major challenges.

Literature Review

Scoring refers to a method of assigning a numerical value (the 'score') to a client in order to predict how he or she is likely to behave relative to others in terms of some action in the future. By analysing a sample of past (historical) client and business data, trends are deduced to better understand (potential) clients and predict future events such as credit repayment (Vidal & Barbon, 2019). Credit scoring is a scientific method of assessing the credit risk associated with

new credit applications. It uses quantitative measures of the performance and characteristics of past loans to predict the future performance of loans with similar characteristics (Caire & Kossman, 2003).

Through credit scores, financial institutions can use scoring models to assess a borrower's credit risk and support credit evaluation. These scores assess a person's creditworthiness, or the likelihood they will repay a loan. Furthermore, credit scoring is the cornerstone of the financial industry, influencing access to loans, mortgages, credit cards, and various financial services (Bhat et al., 2023). Information necessary in credit scores comes from socio-demographic data such as gender, age, civil status, business experience, time residing at current residence, type of residence; behavioural data which may include number of days a client is delinquent; Credit Reference Bureau (CRB) data which includes personal credit history with other financial institutions or utility companies; Psychometric data which determines a person's knowledge, abilities, attitudes, and personality traits; and lastly, big data which includes information from phone companies, utilities, retailers or social networks (Facebook, Twitter, LinkedIn, Yahoo!) (De Cnudde, et al., 2019).

Credit scoring models are not intended to replace loan officers and other commercial staff but to complement and facilitate their work by supporting the assessment of willingness to pay (ACCION, 2016). Similarly, credit scoring cannot predict individual loan losses; rather, it predicts the likelihood or odds of a 'bad' outcome (Caire & Kossman, 2003).

According to Palmer and Torgerson (1999), efficiency is concerned with the relationship between resource input costs (labour, capital, or equipment) and their intermediate outputs. Resource efficiency describes minimizing material inputs to maximize economic outputs (van Ewijk, 2018). In credit scoring, efficiency refers to how effectively the system processes applications and makes credit decisions. When an organization first uses data, it can be complicated and time-consuming. Once adopted, however, significant improvements in business efficiency and cost savings occur; the ability to identify and capitalize on new opportunities improves; there is better, customer-focused service; quick Processing of many applications, minimizing the costs associated with manual credit evaluation and optimizing resource utilization in order to obtain better overall performance and reduced wastages (Vidal & Barbon, 2019).

Accuracy refers to how close an instrument's reading is to the true value when measuring a signal or other physical quantity (Arbiter Systems, 2024). In credit scoring, accuracy refers to the scoring system's ability to correctly predict the likelihood that a borrower will repay a loan. In this, the credit scoring system classifies borrowers into either low-risk or high-risk based on their creditworthiness; minimizes errors by reducing both false positives (approving loans to high-risk borrowers) and false negatives (rejecting loans to low-risk borrowers); and accurately predicts defaults and improves loan portfolio performance/health (Caire & Kossman, 2003).

Salter (2023) explained the use of Artificial Intelligence and its Applications in Behavioural Credit Scoring, noting that adoption of machine learning methods remains minimal in financial risk management. Therefore, as deep learning methods have been evaluated for behavioural credit scoring based on performance, research has not holistically evaluated these models on both performance and explainability. In conclusion, given the strict regulatory environment, banks have been hesitant to implement machine learning or deep learning models, especially those that lack sufficient explainability to meet regulatory requirements. To confirm this, this study examines whether digital lending companies in Kenya implement regulatory frameworks that recognize the transparency and explainability of traditional credit scoring methods.

Addy et al. (2024), in their comprehensive review of AI models and predictive analytics in credit scoring, examined the historical context, the transformation of traditional credit assessment methodologies, various AI models used, and the real-world implications of AI in

credit scoring. They aimed to explore AI's transformative impact on credit scoring, highlight the strengths and limitations of different AI models, examine the integration of alternative data sources, discuss the role of explainable AI, and address the ethical considerations associated with AI models in credit scoring. To achieve these objectives, the authors synthesized existing literature on AI in credit scoring. In particular, they examined various AI models and evaluated their effectiveness, scalability, and interpretability. Ultimately, Addy et al. (2004) concluded that AI has significantly improved credit scoring accuracy and efficiency. However, the authors also observed that AI in credit scoring has positive implications for financial inclusion and risk management but requires careful attention to ethical considerations and potential biases. Although the results were remarkable, the study also noted the need for further research on the long-term impact of AI in credit scoring, the scalability of AI models, and their applicability across different financial contexts. Building on this, this study examines the AI perspective in Kenya's digital lending sector.

Tyagi (2022) analysed machine learning models for credit scoring with explainable AI and optimizing investment decisions in the USA. Because of regulatory requirements and the need for trust in automated decision-making in financial services, the study aimed to improve the transparency and predictive power of machine learning models used for credit scoring by employing explainable AI techniques such as SHAP (Shapley Additive Explanations) and LIME (Locally Interpretable Model-Agnostic Explanations). Using data from the Lending Club website for 2016, the author analysed about 110,000 records using logistic regression; the results showed that explainable AI techniques like SHAP and LIME improved the transparency of complex machine learning models. In conclusion, the author observed that explainable AI can significantly enhance the transparency and trustworthiness of machine learning models used in credit scoring. As an area for further study, Tyagi (2022) recommended incorporating more diverse data sources and testing the models in different financial contexts to validate their robustness and generalizability. Accordingly, this study will compile information from diverse sources and conduct an analysis to assess the robustness and generalizability of AI use within digital lenders in Kenya.

Grennepois and Robin (2019) studied artificial intelligence (AI) and machine learning for credit risk management in France. They explored methods to improve model accuracy and explainability. The study aimed to improve the predictive power and explainability of credit risk models while addressing the trade-off between accuracy and transparency in AI applications. It used Shapley value analysis and a hybrid approach combining logistic regression with machine learning models such as Random Forest and Neural Networks. The results show that credit amount, borrower age, and loan duration significantly affect credit scores. In conclusion, the authors observed that model explainability and transparency are crucial for quantifying model risk, as financial institutions can better manage and stress-test models by understanding their sensitivity to variables. As a recommendation, financial institutions should use hybrid approaches that combine traditional and advanced AI models to balance accuracy and interpretability. Although this study used Shapley value analysis, it is computationally intensive, especially with a large number of features, observations, and complex models.

Schmitt and Roper (2023) conducted a study on artificial intelligence (AI)-enabled credit scoring in banking and FinTech in order to unearth the maximum prediction accuracy in the UK. Their objective was to improve the prediction accuracy in credit risk assessment among financial institutions. Such a study was critical to mitigate potential financial losses from defaults, enhance competitive positioning, and strengthen overall financial stability. Their study employed Logistic Regression, Random Forest, Gradient Boosting, and Deep Learning. The dataset included real-world credit-risk data for training and evaluation. The results show that machine learning performance depends on the underlying dataset. Similarly, combining the base models into a super learner improved prediction accuracy across all datasets. In

conclusion, super learning effectively enhances the performance of individual AI/ML models in credit scoring. As a recommendation for further studies, Schmitt and Roper (2023) observed that integrating unstructured data, such as social media activity or transactional text data, should enhance prediction accuracy. Similarly, they recommended incorporating bias and fairness considerations in credit scoring models to ensure equitable lending practices. To advance these recommendations, this study will investigate the relationship between social media, transactional text, and AI prediction accuracy.

Khemakhem and Boujelbene (2017) evaluated the effectiveness of artificial neural networks (ANN) and support vector machines (SVM) for credit risk assessment in Tunisia and compared them with traditional statistical methods. Using data from 408 borrowers, they found that ANN outperformed both SVM and traditional methods in accuracy (90.2%) and in reducing type I errors. They concluded that AI, especially ANN, offers a more reliable alternative for credit scoring and recommended that financial institutions adopt it. However, the study's findings were limited by its focus on a single Tunisian bank. In contrast, the current study aims to include all registered digital lenders in Kenya to enhance the generalizability and relevance of its findings on AI's impact on financial stability.

Moscato and Sperlì (2023) developed benchmark machine learning models for credit scoring using data from the Lending Club social lending platform. Their study aimed to improve creditworthiness predictions by addressing data imbalance and applying Explainable AI (XAI) tools for model interpretability. Using 877,956 samples and 151 features, they applied various sampling strategies and found that the Random Forest model with random under-sampling yielded strong AUC and specificity despite lower accuracy. They concluded that their approach effectively improved credit-scoring predictions and recommended further research on sampling techniques and XAI to enhance model trustworthiness and interpretability.

Sadok et al. (2022) examined AI's role in transforming credit scoring and risk assessment in the U.S. mortgage market. Their study highlighted AI's potential to enhance decision-making through big data while also addressing its socio-economic implications, particularly issues of bias, opacity, and ethical concerns. They concluded that although AI can improve credit risk assessment and promote financial inclusion, it also poses significant legal and ethical risks. The authors emphasized the need for transparency, accountability, and regulatory oversight to mitigate these challenges. Building on this, the current study will empirically assess AI's benefits in credit scoring and examine regulatory compliance among digital lenders in Kenya.

Gambacorta et al. (2024) studied the impact of machine learning and non-traditional data on credit scoring and the effectiveness of these models in predicting borrower defaults and losses in China. Their study compared the predictive power of machine learning and non-traditional data-based credit scoring models with traditional credit scoring models, especially during periods of economic shock. They used descriptive statistics and quantile regression to compare models during normal times and an exogenous regulatory shock. Using 343,976 observations across variables including default dummy, loss rate, fintech credit score, and other financial and demographic metrics, the results showed that machine learning models based on non-traditional data outperformed traditional models in predicting losses and defaults, particularly after a regulatory shock. They concluded that machine learning models using non-traditional data are more effective in credit scoring, especially in volatile economic conditions. As a recommendation, they argued that there is a need for financial institutions to incorporate machine learning techniques into their credit scoring processes, an aspect this study investigated.

Theuri and Olukuru (2022) examined AI implementation in banking, particularly through a dashboard that aggregates key financial data and insights for decision-makers in Kenya. The study explored how AI and machine learning (ML) applications are transforming the banking industry by enhancing decision-making and improving operational efficiency. Using anonymized financial data (1,056,320 transaction records and 5,369 client records) from a

Czech bank, the authors used Microsoft Power BI for data visualization and analysis. The results showed that AI provided real-time insights through dynamic dashboards, enhancing decision-making in banks. Based on these results, the authors concluded that AI significantly improves the banking sector's ability to analyse data, forecast trends, and make informed decisions, ultimately leading to better customer service and risk management. As a recommendation, there is a need for banks to invest in the necessary infrastructure to support AI and ML applications effectively. Similarly, banks need to build data science and engineering skills and knowledge to support AI applications in banking. Given the challenges in the real-world application of these models due to the need for specialized software and hardware, this study will investigate the level of investment devoted to supporting AI within digital lenders in Kenya.

Akello (2022) outlined AI applications across sectors, the challenges faced, the risks to human rights, and recommendations to mitigate these risks. The study aimed to explore AI's impact on human rights and identify the challenges and risks associated with AI adoption in Kenya. Through a literature review, an analysis of AI applications in key sectors, and an assessment of the regulatory framework on data protection and AI ethics, the findings revealed that AI systems require large datasets, including personal and sensitive data, to function effectively. Similarly, restricting access to data creates significant risks of bias and discrimination in AI outputs. Lastly, although compliance with the Data Protection Act is crucial, it may hinder innovation if not balanced properly. In conclusion, this policy brief indicates that adopting AI in Kenya presents both opportunities and challenges, particularly regarding human rights and ethical considerations. Similarly, there is a need for clear guidelines and frameworks to ensure responsible AI use. As a recommendation, there is need for the government to implement measures to protect human rights while fostering AI innovation; the workforce should have its capacity built to effectively utilize AI technologies as well as the need to establish clear regulatory frameworks to guide the ethical use of AI and data protection. Although this study explored AI use and its potential risks to human rights, it will now examine its use among digital lenders.

Ampountolas et al. (2021) studied the application of machine learning techniques to improve credit scoring in micro-finance institutions (MFIs) in Africa. To evaluate the effectiveness of machine learning models in assessing defaults in micro-credit lending, especially in the absence of centralized credit databases, the authors used various machine learning algorithms to analyse data and predict defaults. The trials found that machine learning algorithms effectively extracted hidden information from datasets, helping assess defaults in micro-credit. Based on these results, they concluded that machine learning techniques can significantly enhance credit scoring in microfinance, providing a viable alternative to traditional methods that rely on historical credit data. Given this, Ampountolas et al. (2021) recommended further exploring machine learning methods in financial contexts, particularly for institutions serving unbanked populations. They also suggested improving data collection practices to enhance model training. Following this recommendation, this study focused on fintech lenders that primarily advance credit to unbanked populations.

Kshetri (2021) investigated the role of AI in promoting financial inclusion, addressing regulatory compliance, fraud reduction, risk assessment, and improving collection processes within the developing countries of Malaysia, Chile, and Indonesia. The study aimed to explore how AI can enhance financial inclusion for unbanked populations in developing countries and to identify the challenges and opportunities of implementing it. Using qualitative analysis of existing AI applications in financial services, along with case studies and examples from various FinTech companies, the results indicated that AI tools can help financial institutions comply with regulations, reduce fraud, and assess lending risks effectively. Hence, the researcher concluded that while AI has the potential to significantly improve financial inclusion, its current application in developing countries remains in the early stages, with many

projects still at the prototyping level. As a recommendation, it is imperative to invest in AI talent development and training for financial institution staff; encourage regulatory frameworks that support AI adoption while addressing privacy and employment concerns; there is need for continued research and development of AI applications tailored to the specific needs of developing markets. Although Kshetri (2021) focused on Malaysia, Chile, and Indonesia, this study focused on Kenya, a developing African nation.

Methodology

This paper adopted a descriptive research design and opted for a mixed-method approach, which incorporated a structured surveys and interviews. A census approach was adopted. However, data were gathered from 30 of Kenya's 32 regulated digital lenders. This represented a 94 percent response rate. Similarly, Cronbach's alpha of 0.709 (Appendix 2) also indicated that the information was reliable. The results in the graphs below provide insights across three thematic areas: (1) credit scoring accuracy and effectiveness, (2) processing efficiency, and (3) customer and institutional outcomes. The descriptive data analysis in this study helped organize raw data into meaningful information using averages, frequencies, and percentages. This helps technical and non-technical audiences interpret the results easily. Similarly, the easy-to-understand results lay a groundwork for deeper statistical analysis.

Effect of AI on Credit Scoring Accuracy and Effectiveness

This objective was undertaken to assess respondents' perceptions of how AI could improve credit scoring accuracy and effectiveness, especially in loan repayment and loan defaults. Figure 1 contains the results.

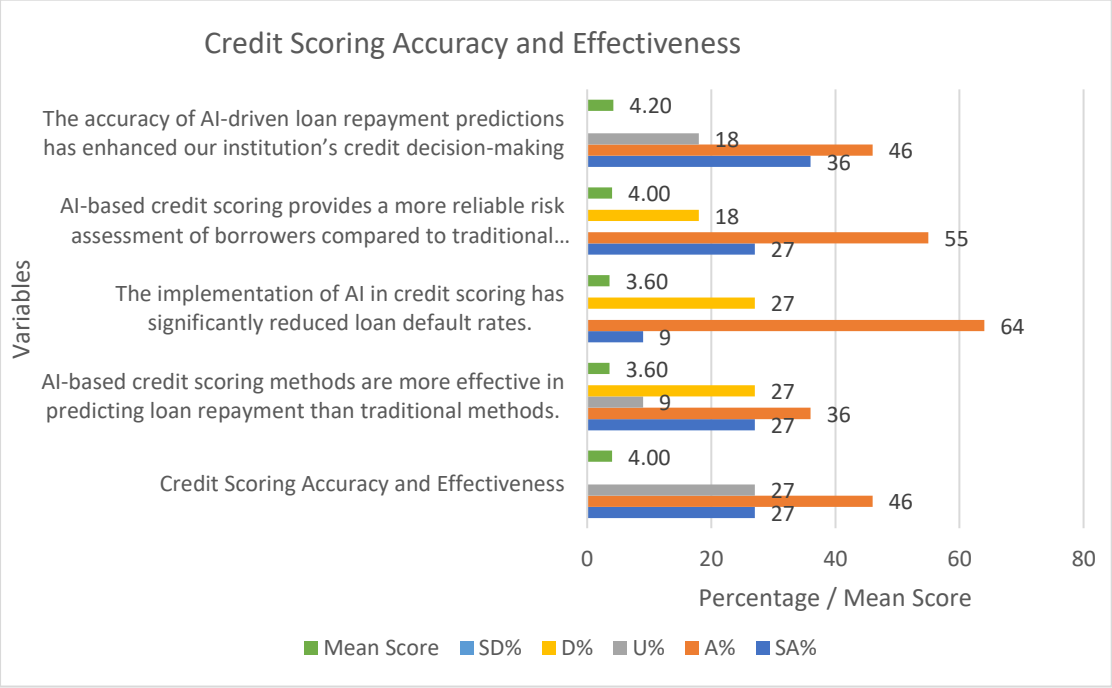


Fig.1: Effect of AI on Credit Scoring Accuracy and Effectiveness

Regarding credit scoring accuracy and effectiveness, most respondents expressed strong confidence in AI's role in improving lending decisions. Specifically, 82 percent of participants, with a mean of 4.2, agreed or strongly agreed that AI-based credit scoring improves credit decision-making. Similarly, a high proportion (82%) endorsed the view that AI provides a more reliable assessment of borrower risk compared to traditional methods (mean = 4.0). Sixty-three percent of the respondents (with a mean of 4.0) believed that AI is more effective than

conventional techniques. Overall, 73 percent (with a mean of 4.0) agreed that AI enhances the overall accuracy and effectiveness of credit scoring. These results are in consonance with Bhat et al. (2023) and Addy et al. (2024), who also recognized the significance of AI in enhancing the accuracy and efficiency of credit scoring. However, when asked whether AI has led to a reduction in loan default rates, the level of agreement declined. Only 73 percent supported this statement, and the item recorded the lowest mean score (3.6), suggesting a perceived gap between AI's predictive capabilities and its influence on borrower repayment behaviour. This finding also corroborates Caire and Kossman (2003), who asserted that AI's use in Credit scoring cannot predict individual loan loss.

The analysis in Table 1 also indicated that Credit Scoring Accuracy and Effectiveness had a perfectly symmetrical distribution (Skew =0) with fewer extreme values, suggesting that its tail was flatter than normal (Kurtosis= -1.111). Hence, it was noted that the predictive precision of AI alone is not enough to cause a behavioural change among borrowers.

Table 1: Descriptive Statistics

	CSAE	PE	CIO
Mean	4	4.36	4
Skewness	0	0.661	-1.578
Kurtosis	-1.111	-1.964	5

Effect of AI on Processing Efficiency

This objective gauged respondents' perception of AI's processing efficiency in loan approvals and loan applications. Results are as per Figure 2.

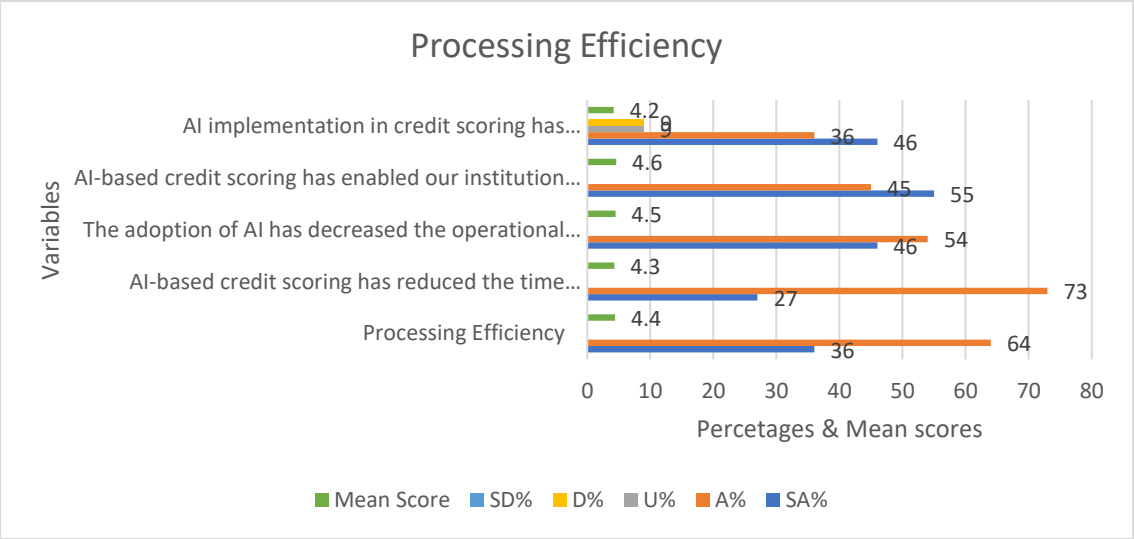


Fig.2: Effect of AI on Processing Efficiency

Based on AI's effectiveness on processing efficiency, respondents showed an overwhelmingly positive consensus. One hundred percent of respondents either agreed or strongly agreed that AI enables processing a higher volume of loans daily, reduces the cost per loan application, and shortens loan processing time, with mean scores of 4.6, 4.5, and 4.3, respectively. This aligns with Vidal and Barbon (2019), who also noted that AI speeds up the processing of many applications. Additionally, 82 percent acknowledged AI's ability to streamline the loan approval process (mean = 4.2).

These results emphasize the value of AI in optimizing internal workflows, reducing human error, and enhancing turnaround times. These are critical success factors in the competitive digital lending environment; thus, this view aligns with Addy et al. (2024), who also found that AI enhances efficiency. Overall, the results indicated that through AI adoption, there has been a significant efficiency in operations, especially in quick loan processing and reduced costs.

Customer and Institutional Outcomes

To assess AI's role in supporting customer and institutional outcomes, such as risk weighting, transparency, customer satisfaction, and fairness and bias, Figure 3 outlines the results.

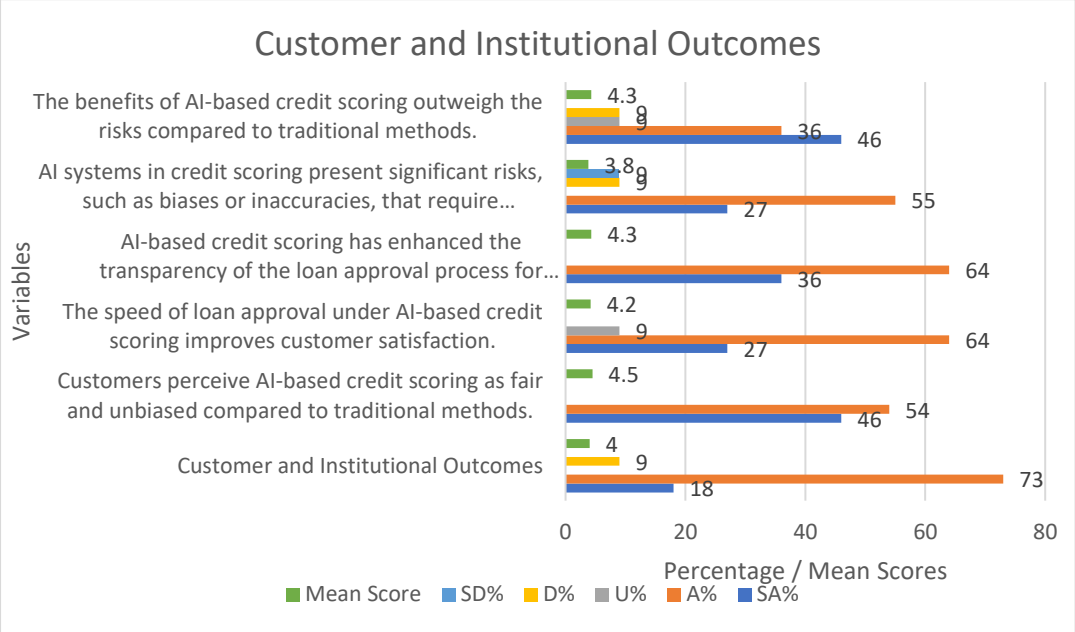


Fig. 3: Effect of AI on Customer and Institutional Outcomes

On customer and institutional outcomes, most respondents recognized AI's benefits from both service delivery and risk management perspectives. A substantial majority (90%) agreed that AI improves customer satisfaction due to faster loan processing (mean = 4.3). Similarly, 80 percent acknowledged that AI systems carry risks such as algorithmic bias and inaccuracies that require deliberate management (mean = 4.3). This result aligns with Addy et al. (2024), who also emphasized the need to address ethical concerns and potential biases in AI use in credit scoring. Interestingly, 82 percent also believed that AI's overall benefits outweigh its risks (mean = 4.3), indicating a cautiously optimistic stance among employees.

Transparency in loan approval processes was another area where AI was viewed favourably, with 100 percent of respondents agreeing that AI enhances transparency (mean = 4.2). This result aligns with Tyagi's (2022) finding that AI can significantly enhance the transparency and trustworthiness of machine learning models used in credit scoring. However, while respondents were positive about AI's fairness, the statement on whether customers perceive AI-based decisions as fairer than traditional methods received a relatively lower mean score of 4.0. This suggests that while employees recognize AI's potential for fairness, lingering concerns about customer trust and understanding of AI-driven processes undermine Tyagi's (2022) claim that AI enhances transparency. With 80 percent acknowledging risks like algorithmic bias alongside high satisfaction, this contradiction suggests respondents recognize bias but still strongly support AI adoption. As a result, respondents underweight the risks relative to perceived efficiency gains.

Conclusion and Recommendation

In conclusion, respondents strongly believe AI-based credit scoring is effective, efficient, and beneficial, though they have slightly less confidence in its direct impact on reducing loan default rates. Additionally, there is an acknowledgment of potential risks like bias and inaccuracy regarding the use of AI; hence, the need for its further development and careful management.

As a recommendation, digital lending institutions should continue adopting and integrating AI-based credit scoring systems to improve efficiency and decision-making. However, to address concerns about bias, inaccuracy, and limited impact on loan default reduction, there should be a continuous improvement of AI systems by regularly evaluating the different models in the market and including diverse data inputs, especially psychometric data, to assess an individual's honesty and reliability. The model should also include a social credibility score (association with those with good repayment records). Furthermore, institutions should establish clear ethical guidelines and regulatory compliance frameworks to ensure responsible and transparent use of AI in credit scoring.

Acknowledgment

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Integration of Artificial Intelligence in Investments and Corporate Finance: Transformations, Challenges, and Future Prospects in the Financial Industry

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Abstract
Artificial Intelligence (AI) has emerged as a transformative force in corporate finance and investment management. This paper examines its role, challenges, and future prospects using an integrative review methodology. Guided by Customer Relationship Management Theory and Christensen's Disruption Theory, and using Abstrackr, we systematically reviewed 44 peer-reviewed studies selected through explicit inclusion and exclusion criteria. The analysis revealed that AI-driven technologies such as machine learning, natural language processing, and robotic process automation are revolutionizing risk assessment, fraud detection, financial forecasting, tax planning, investment advisory, and sentiment analysis. These tools improve efficiency, enhance accuracy, and provide real-time decision support in the financial sector. Despite these advances, adoption is hindered by challenges including data security risks, algorithmic bias, ethical concerns, regulatory compliance gaps, and workforce skill shortages. Furthermore, gaps remain in addressing the intersections of Explainable AI (XAI), Generative AI, and AI-cybersecurity, which are increasingly relevant to finance. Future opportunities include leveraging emerging AI frontiers such as quantum AI, decentralized finance (DeFi), and Blockchain-based ecosystems to improve transparency and accountability. The study contributes by synthesizing current knowledge and proposing a conceptual framework linking AI applications to transformations and challenges in finance. Findings offer practical guidance for financial institutions, policymakers, and practitioners on adopting AI responsibly while mitigating risks. We conclude that AI's disruptive influence will expand further, necessitating adaptive regulation, workforce reskilling, and interdisciplinary collaboration to ensure sustainable innovation in finance.

Keywords: Artificial Intelligence, fraud detection, portfolio optimization, predictive analytics, risk assessment
JEL Classification: C45, O33, D53, G17

Introduction

The integration of Artificial Intelligence (AI) into corporate finance has revolutionized financial practices by improving efficiency, automation, and predictive capabilities. AI is increasingly used for fraud detection, financial forecasting, tax compliance, risk management, and investment advisory services. While its potential benefits are significant, challenges related to data security, ethics, algorithmic bias, and regulatory compliance remain unresolved.

What role does AI play in reshaping the finance industry through applications such as predictive analytics, fraud detection, investment management, and compliance, and what challenges arise from this integration? This paper addresses this question through an integrative review of recent literature and develops a conceptual framework to illustrate the connections between AI technologies, applications, transformations, challenges, and outcomes.

Theoretical Framing

The paper is grounded in two key theories. First is customer relationship management (CRM) theory, which emphasizes AI's role in enhancing customer interactions through personalized financial services, real-time support, and predictive analytics. This theory suggests that AI-driven tools can improve customer retention, engagement, and satisfaction by leveraging big data analytics to create highly tailored financial solutions (Buttle, 2009; Payne & Frow, 2017). AI-enabled CRM systems can automate customer service responses, track consumer behaviour, and enhance relationship marketing strategies. Recent research underscores the role of AI-driven Chatbots and virtual assistants in improving interactions in financial services (Pothapala & Yadav, 2024).

Secondly, Christensen's disruption theory explains how technological innovations disrupt traditional financial management practices by offering competitive advantages through automation and predictive decision-making (Christensen, 1997). Disruptive innovations initially emerge in niche markets before transforming entire industries, as seen with AI-powered financial advisory services, algorithmic trading, and automated risk assessment tools (Rayna & Striukova, 2016). Integrating AI into financial management represents a paradigm shift in how businesses approach decision-making, investment strategies, and operational efficiency. Recent literature suggests that AI's disruption of financial markets is accelerating, with robo-advisors and AI-enhanced trading systems outperforming traditional models (Dakalbab et al., 2024).

Conceptual Framework

The conceptual framework for this study illustrates the pathways through which Artificial Intelligence (AI) influences corporate finance and investment management. It builds upon Customer Relationship Management theory and Christensen's Disruption Theory, extending them to highlight both the transformative benefits and emerging challenges of AI adoption in the financial industry.

As shown in Figure 1, AI technologies such as machine learning, natural language processing, robotic process automation, explainable AI, generative AI, and quantum AI form the foundation of integration in finance. These technologies support a wide range of applications including risk assessment and management, fraud detection, financial forecasting, automated tax planning, investment advisory, and financial market sentiment analysis.

These applications drive significant transformations in the financial sector, including greater efficiency, improved accuracy, process automation, and enriched customer experiences. However, they also introduce key challenges, including cybersecurity risks, ethical concerns, algorithmic bias, regulatory compliance issues, and workforce adaptation needs.

The framework further identifies the expected outcomes of AI adoption in finance: sustainable adoption, responsible innovation, and enhanced decision-making. This conceptualization provides the basis for synthesizing the reviewed literature and analysing both opportunities and risks associated with AI in corporate finance.

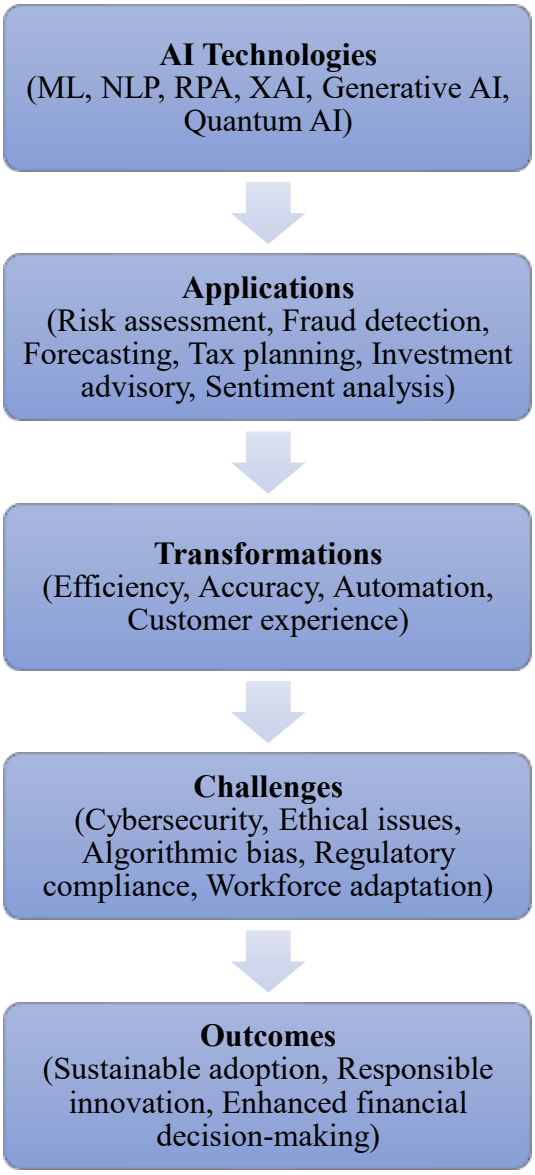


Fig. 1: Conceptual Framework

Methodology

Systematic reviews are a structured, reproducible method for synthesizing existing research to answer a clearly formulated question. They involve identifying, selecting, and critically appraising all relevant studies on a specific topic, ensuring transparency and replicability. The goal is to provide a comprehensive overview of the evidence and to inform evidence-based decisions and practices (Tawfik et al., 2019).

They are a type of evidence synthesis in which authors develop explicit eligibility criteria, collect all available studies that meet these criteria, and summarize results using reproducible methods that minimize bias and error (Tawfik et al., 2019). They serve different purposes and use a different methodology than other types of evidence synthesis, such as narrative reviews, scoping reviews, and overviews of reviews (Munn et al., 2018). These reviews can address questions about the effects of interventions or exposures, the diagnostic properties of tests, and the prevalence or prognosis of diseases.

Rigorous systematic reviews follow common processes, including (Brignardello-Petersen et al., 2025) determining the question and eligibility criteria, including a priori specification of subgroup hypotheses; searching for evidence and selecting studies; abstracting

data and assessing the risk of bias of the included studies; summarizing the data for each outcome of interest, whenever possible using meta-analyses; and assessing the certainty of the evidence and drawing conclusions. Several tools can guide and facilitate the systematic review process, but methodological and content expertise are always necessary for success.

Using Abstrackr, a free, open-source screening software developed at Brown University, the study gathered, reviewed, and evaluated relevant papers, reports, and existing literature on the topic of interest (Wallace et al., 2012). It conducted a thorough search across academic databases, online repositories, journals, and official websites for relevant research papers on the influence of various AI variants in the financial industry.

This paper prioritized current research and publications using Abstrackr's stringent inclusion and exclusion criteria. This included findings, approaches, important concepts, and empirical evidence. This resulted in 73 relevant articles and research reports on AI in accounting, audit, and finance. This list was later narrowed to 44 high-quality scholarly documents in the financial industry for review. To identify common themes, trends, obstacles, and best practices, and to select key components of the profitability of property developers in Kenya, the data was gathered and then thematically organized for qualitative analysis.

AI Transformations in the Financial Industry

AI is significantly transforming operations and activities in the financial industry in many ways. What follows is a discussion of these transformations to better understand these trends.

Financial risk assessment and management is an important area in which AI is transforming the financial industry. AI enables financial institutions to evaluate and mitigate risks through predictive modelling and real-time analysis of financial trends. Advanced machine learning models assess creditworthiness, forecast market trends, and enhance risk mitigation strategies. These models enable proactive risk management by analysing vast datasets and identifying patterns that human analysts may overlook (Abbadi & Alawneh, 2008; Abellán & Castellano, 2017; Al Ameri & Nobanee, 2021; Ahmed et al., 2020). AI's role in risk assessment is expanding as more sophisticated deep learning models improve credit scoring accuracy (Nguyen et al., 2023).

AI therefore, acts as a core mechanism for protecting institutional capital through real-time anomaly detection and predictive risk forecasting (Ozili, 2025). Machine learning architectures analyze extensive transaction histories to identify structural patterns indicative of financial statement manipulation, insider trading, or identity theft (Bakar & Pasiouras, 2020). Furthermore, banks and corporate financial teams employ unsupervised learning algorithms to chart complex interconnections within credit portfolios, improving bankruptcy forecasting models and isolating systemic risk vectors that traditional audit systems fail to flag (Aziz et al., 2022; Ozili, 2025).

AI is also making a significant contribution to fraud detection and prevention in the financial industry. AI-powered systems analyse transaction patterns to detect anomalies and potential fraud, thereby reducing financial losses. AI utilises deep learning techniques to recognise unusual spending behaviours and flag potentially fraudulent activities in real time, thus strengthening financial security frameworks (Albashrawi, 2021; Bahnsen et al., 2013; Bhingarde et al., 2015; Mossavar Rahmani, 2023; Xiaojing, 2021). Researchers are also exploring the application of Blockchain technology alongside AI to further enhance fraud detection mechanisms (Rane et al., 2023)**.**

Financial forecasting and predictive analytics have become a key application of AI in the financial industry. AI improves the accuracy of financial forecasting by analysing vast datasets, allowing companies to make data-driven investment decisions. AI-driven predictive analytics help organisations optimise budget planning, revenue forecasting, and financial decision-making by identifying economic trends and fluctuations (Banu et al., 2023; Khedr et al., 2017; Patel et al., 2015; Sharafi et al., 2016; Soleimani, 2018). Recent research suggests that AI is

enhancing stock market forecasting through hybrid AI models that integrate natural language processing with quantitative financial analysis (Nguyen et al., 2023).

Automated tax planning is increasingly being transformed by AI, which simplifies tax compliance by automating data collection, ensuring accuracy, and optimising tax-saving strategies. AI-powered tax systems streamline processes such as tax documentation, audits, and compliance, reducing human errors and increasing efficiency (Chen & Du, 2009; Hapsari & Puspitasari, 2024). AI-driven tax platforms now incorporate real-time legislative updates to ensure compliance with evolving tax laws (Han et al., 2023).

Personalized investment advisory services have emerged as a significant application of AI in the financial industry. Robo-advisors use AI to analyse market trends and provide personalised investment recommendations. AI-driven investment platforms assess investors' risk appetites, financial goals, and market conditions to offer tailored investment strategies, making wealth management more accessible (Al-Blooshi & Nobanee, 2020; Cheng, 2016; Cheng et al., 2017; Harsono & Suprapti, 2024). Wealth management firms are therefore leveraging generative AI and algorithmic innovations to democratize personal financial planning (Swanger, 2024). Automated robo-advisory platforms maintain continuous availability, utilizing large language models and machine learning to evaluate individual customer risk tolerances, income constraints, and long-term financial goals (Karamchandani, 2025). This technology therefore allows firms to scale hyper-customized investment portfolios, automate recurring tax-loss harvesting workflows, and execute digital rebalancing cycles at a fraction of the cost of traditional wealth management (Citi GPS, 2025; ESMA, 2026).

Portfolio management and optimization has truly benefited from advances in AI. Artificial intelligence has fundamentally transformed portfolio construction and asset allocation by moving beyond traditional linear financial models like the Capital Pricing Model. Through deep learning frameworks such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), AI systems process vast datasets in real time to capture complex, non-linear market behaviours and automatically adjust allocations (ESMA, 2026). Financial institutions deploy these algorithms to consistently optimize the risk-return profile of diversified portfolios, dynamically shifting capital to higher-performing asset classes as real-time market data fluctuates (Citi GPS, 2025; Karamchandani, 2025).

Sentiment analysis and alternative data processing is another area where AI algorithms have become handy in corporate finance and investment markets. Advances in AI-driven portfolio management now integrate sentiment analysis to refine investment strategies based on fluctuations in market sentiment (Dakalbab et al., 2024). The integration of natural language processing (NLP) has revolutionized how the financial industry processes unstructured data (Swanger, 2024). AI algorithms continuously ingest millions of textual and visual sources, including corporate earnings call transcripts, financial news feeds, regulatory filings, and social media commentary (Citi GPS, 2025). By performing contextual sentiment analysis, these platforms score emotional opinions and identify market perceptions, giving investment managers early warnings or predictive insights regarding stock price trajectories before the metrics reflect on public balance sheets (ESMA, 2026; Raimundo & Rosário, 2026).

Financial market sentiment analysis has therefore become an increasingly important application of AI in financial decision-making. AI tools assess market sentiment by analysing news articles, social media, and financial reports to predict stock market movements. These AI-driven systems enhance decision-making by extracting insights from large volumes of textual and numerical data (Al-Shabandar et al., 2019; Patel et al., 2020; Popkova & Parakhina, 2019). Recent developments in AI-based sentiment analysis incorporate advanced neural networks to improve sentiment-classification accuracy (Nguyen et al., 2023).

Algorithmic and high-frequency trading in the financial industry has emerged and is now widely used. In the realm of capital markets, advanced machine learning and reinforcement learning models drive autonomous, high-speed trading architectures (Raimundo & Rosário,

2026). These AI-driven automated trading systems analyze real-time market parameters, historical price movements, and liquidity constraints simultaneously to generate precise trade signals (Bakar & Pasiouras, 2020). By removing human emotional biases and executing transactions within microseconds, these systems mitigate the market impact costs of large block orders and successfully capture transient alpha opportunities in highly liquid markets (Aziz et al., 2022).

To provide a consolidated view of AI's role in investments and corporate finance, Table 1 summarizes the main applications, their benefits, and associated challenges.

Table 1: Applications, Benefits and Challenges of AI in the Financial Industry

AI Application	Benefits	Challenges
Risk Assessment & Management	Improved credit scoring; proactive risk Management	Algorithmic bias; data privacy
Fraud Detection	Real-time anomaly detection; reduced losses	Data security; evolving fraud techniques
Financial Forecasting	Accurate predictions; data-driven decisions	Over-reliance on models; explainability
Tax Planning	Automation of compliance; efficiency gains	Legal/regulatory complexity
Investment Advisory	Personalized strategies; robo-advisors	Transparency; investor trust
Sentiment Analysis	Market insight from big data	Data authenticity; interpretation challenges
Cybersecurity (AI-driven)	Strengthened systems; predictive defence	Constantly evolving threats
Generative & Quantum AI	New models for financial innovation	Immaturity of technology; regulation gaps

Emerging Challenges and Ethical Considerations

Despite AI's benefits in financial management, several challenges persist. First, data security and privacy remain concerns. AI relies on vast amounts of sensitive financial data, heightening concerns about data breaches and cybersecurity risks. Ensuring data protection is crucial for AI-driven financial management systems (Albashrawi, 2021). Second, regulatory compliance is a challenge. AI's rapid advancement outpaces existing regulatory frameworks, creating legal uncertainties and compliance challenges. Policymakers must establish regulations that balance innovation with accountability.

Policymakers must also address algorithmic bias and fairness concerns. Most AI models may exhibit biases that affect financial decision-making, leading to discriminatory practices in credit scoring, lending, and investment recommendations. Addressing algorithmic bias is essential for ethical AI deployment. Lastly, workforce adaptation and skill gaps pose significant challenges. AI-driven automation may displace traditional financial roles, necessitating workforce upskilling and reskilling. Financial professionals must adapt to AI-driven decision-making processes.

Conclusion and Considerations for Policy

Artificial Intelligence is transforming investments and corporate finance by improving efficiency, accuracy, and decision-making across domains such as risk assessment, fraud

detection, financial forecasting, tax planning, and investment advisory services. AI-driven technologies, including machine learning, natural language processing, and robotic process automation, have revolutionized traditional financial practices, delivering significant benefits to financial institutions and businesses. However, these advancements also pose challenges, including data security concerns, regulatory compliance issues, algorithmic bias, and workforce adaptation.

To fully harness AI's potential while mitigating its risks, financial institutions and markets will need to implement robust data protection measures, establish ethical AI governance frameworks, and ensure regulatory compliance. Upskilling the workforce and fostering interdisciplinary collaboration between financial experts and AI specialists will be critical to navigating this technological shift. Moreover, financial markets regulatory bodies must evolve their frameworks to balance innovation and accountability and foster responsible AI adoption.

AI's role in investments and corporate finance is expected to evolve, with advancements in quantum computing, deep learning, and explainable AI enhancing financial decision-making. Emerging trends include AI-powered financial ecosystems, decentralized finance (DeFi), and Blockchain-based financial services.

The future of AI adoption in the financial industry seems promising. Regulatory frameworks will therefore need to adapt continuously to address AI-related risks while fostering responsible innovation. Collaboration among financial institutions, policymakers, and technology developers will be crucial to shaping AI's future in financial management. Looking ahead, continued advances in quantum computing, deep learning, and decentralized financial technologies will further reshape the financial landscape. AI-powered financial ecosystems, Blockchain integration, and explainable AI will play pivotal roles in enhancing transparency and trust in investments and corporate finance. By proactively addressing ethical, regulatory, and technical challenges, businesses can maximize AI's benefits and drive sustainable financial innovation.

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