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TECHNOLOGY DRIVEN THEFT MANAGEMENT: EVALUATING THE EFFECTIVENESS OF AI AND MACHINE LEARNING ON IDENTIFYING AND PREVENTING THEFT

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Abstract

This study investigates the impact of Artificial Intelligence (AI) and Machine Learning (ML) technologies on theft identification and prevention in Nigeria. Given the increasing concern over theft in various sectors, the research aims to assess whether AI and ML can significantly enhance the detection and prevention of theft. A sample of 400 respondents was surveyed using a structured Likert-scale questionnaire to gather data on the effectiveness of AI and ML in identifying theft patterns, predicting theft, analyzing large datasets, detecting unusual behaviors, and their cost-effectiveness. A multiple linear regression model was employed to analyze the relationship between the adoption of AI/ML technologies and theft prevention. The findings reveal that AI and ML technologies have a significant positive impact on theft identification and prevention in Nigeria. Specifically, AI's ability to identify theft patterns, predict potential theft, and analyze large datasets significantly enhances theft detection. Additionally, Machine Learning's capacity to detect unusual behaviors further strengthens the prevention mechanisms. While the cost-effectiveness of these technologies is perceived as a challenge, its influence on theft prevention remains significant, albeit with a smaller effect size. The study concludes that AI and ML technologies can be powerful tools in combating theft, offering promising solutions for the Nigerian context. The results underscore the importance of integrating AI and ML in theft prevention strategies and highlight the need for continued investment in these technologies to ensure their effectiveness, particularly in a developing country like Nigeria.

Introduction

The advent of technology has significantly transformed the way organizations manage and mitigate risks, particularly in the area of theft management. Theft remains a critical challenge to businesses, organizations, and individuals, especially in developing nations like Nigeria. Traditional theft prevention methods, such as physical surveillance and manual inventory checks,

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have proven to be inefficient in addressing the complexities of modern theft patterns. Consequently, there is an increasing reliance on technology-driven solutions, such as Artificial Intelligence (AI) and Machine Learning (ML), to combat theft effectively Agrawal, A., Gans, J. S., & Goldfarb, A. (2018).

Sultani, et al. (2018), AI and ML have revolutionized various industries by offering automated systems that can analyze large datasets, recognize patterns, and make predictions. These technologies are now being adopted in theft management systems to identify theft activities in real time, predict potential threats, and ultimately prevent occurrences of theft Asare, P., & Amankwah, (2019). For example, AI-powered video analytics can detect suspicious activities in retail stores, warehouses, and residential areas. Similarly, ML algorithms can be trained to analyze historical theft data to predict patterns and develop actionable insights.

Accruing to Omotayo, (2021), theft poses significant challenges in sectors such as retail, logistics, and the public sector. Weak law enforcement infrastructure, coupled with rising unemployment and economic hardship, has exacerbated the rate of theft and criminal activities. This has necessitated the adoption of innovative, technology-driven solutions to protect assets and resources. The use of AI and ML in theft management offers a promising avenue to address these challenges, yet their effectiveness in the Nigerian context remains underexplored. This study aims to evaluate the role and effectiveness of AI and Machine Learning in identifying and preventing theft in Nigeria.

Theft has remained a persistent problem in Nigeria, leading to significant financial losses, reduced productivity, and heightened security concerns Kumar, A., et al. (2019). Despite the adoption of traditional security measures, businesses and individuals continue to suffer from theft-related issues. Security personnel, manual surveillance systems, and rudimentary alarm systems often fail to detect and prevent theft in real time due to human limitations and outdated technologies Nguyen, et al. (2021). With the rapid advancement of AI and Machine Learning technologies, there is a growing opportunity to address the limitations of traditional theft management systems. AI-driven systems can process vast amounts of data quickly, enabling the identification of unusual patterns and activities indicative of theft. However, there is limited research evaluating the effectiveness of these technologies in the Nigerian context, where factors such as poor infrastructure, inadequate expertise, and financial constraints may hinder their adoption Buolamwini, & Gebru, (2018).

This study, therefore, seeks to investigate the effectiveness of AI and ML in identifying and preventing theft in Nigeria, assessing the feasibility, benefits, and challenges associated with implementing these technologies.

Concept of Theft Management Technologies

Theft management encompasses the strategies, technologies, and processes aimed at detecting, preventing, and responding to theft-related activities. Traditional methods, such as manual surveillance, human guards, and rudimentary alarm systems, have been widely used but have shown significant limitations in efficiency and accuracy. Modern approaches now integrate technology-driven solutions, offering real-time data analytics, automated monitoring, and enhanced accuracy (Singh & Jain, 2020). Traditionally, theft prevention relied heavily on manual surveillance, physical barriers, and basic alarm systems. However, the advent of digital technology and the rise of data-driven decision-making have transformed theft management practices.

The initial wave of technological interventions included Closed-Circuit Television (CCTV) systems and basic motion detection sensors. While these systems provided an additional layer of security, they were largely reactive and required human intervention for monitoring and response (Gill & Spriggs, 2005). The integration of digital recording and remote access capabilities marked a step forward, enabling law enforcement and security personnel to review incidents post-theft more effectively. AI and ML have introduced predictive and proactive elements into theft management. Early implementations involved simple rule-based systems, but advancements in computing power and data availability have enabled the deployment of complex algorithms capable of real-time analysis and decision-making. Modern systems can analyze vast amounts of data from various sources, including video feeds, transactional records, and IoT devices, to identify patterns indicative of theft (Zhang et al., 2018).

Artificial Intelligence and Machine Learning Technologies in Theft Management

AI and ML technologies have been instrumental in advancing theft prevention systems. AI enables systems to analyze massive datasets to detect patterns, while ML improves accuracy by learning from historical data (Brynjolfsson & McAfee, 2017). The use of video analytics**,** facial recognition**,** and anomaly detection algorithms are some of the notable applications in theft management.

Video Surveillance and Analytics

Video surveillance systems powered by AI offer real-time monitoring capabilities. AI-driven cameras can detect suspicious movements and alert security personnel instantly, thereby improving response time (Asare & Amankwah, 2019).

Pattern Recognition

ML algorithms are trained to identify patterns that indicate theft behaviors. For instance, systems can analyze transaction data to flag unusual purchases or behaviors that suggest fraudulent activities (Omotayo, 2021).

Predictive Analytics

Predictive analytics uses historical theft data to forecast potential risks, enabling organizations to implement preventive measures before theft occurs (Ekpo, 2020).

Effectiveness of AI and ML in Theft Management

Studies have demonstrated that AI and ML significantly improve theft detection and prevention. For instance, a study by Singh & Jain (2020) revealed that AI-driven systems reduced theft incidents by 40% in retail environments. Similarly, predictive analytics was found to enhance security by accurately forecasting theft-prone locations and behaviors.

Effectiveness of AI and ML in Theft Management

The effectiveness of artificial intelligence (AI) and machine learning (ML) in theft management has been widely studied and documented across various industries. These technologies have introduced transformative capabilities that significantly enhance the ability to prevent, detect, and respond to theft. By analyzing large datasets and recognizing patterns that humans might overlook, AI and ML technologies have shifted theft management from reactive to proactive approaches. This section explores the diverse applications, benefits, and proven outcomes of AI and ML in mitigating theft, supported by empirical studies and real-world cases.

One of the most prominent applications of AI and ML in theft management is predictive analytics. Predictive analytics leverages historical data to forecast potential theft incidents, enabling organizations to allocate resources more effectively. In the retail sector, for example, AI systems analyze point-of-sale data, inventory logs, and employee schedules to identify anomalies that may indicate internal or external theft. Jain et al. (2020) highlight that retail environments utilizing ML-based predictive models experienced a 30% reduction in shoplifting and internal theft incidents. These systems also excel in identifying high-risk periods or locations, allowing security measures to be concentrated where they are needed most.

Real-time surveillance powered by AI has revolutionized traditional monitoring systems. Computer vision algorithms can process video feeds continuously, identifying suspicious behaviors such as loitering, unauthorized access, or tampering with assets. Sultani et al. (2018) demonstrated that AI-powered surveillance systems achieve higher detection accuracy compared to manual monitoring, with response times reduced by up to 50%. Moreover, facial recognition technology enhances security by identifying known offenders or alerting personnel to unauthorized individuals. In retail settings, these capabilities not only deter potential shoplifters but also improve the efficiency of loss prevention teams. In logistics and transportation, AI and ML have proven effective in reducing cargo theft, a persistent issue that incurs significant financial losses annually. Predictive models in this domain analyze variables such as delivery

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schedules, route characteristics, and historical theft data to identify high-risk scenarios. A study by Chen et al. (2021) revealed that implementing AI-driven predictive analytics reduced cargo theft incidents by 20%. The ability to dynamically adjust routes or schedules based on risk assessments ensures that shipments are safeguarded against potential threats. Additionally, the integration of IoT sensors with AI systems provides real-time tracking and anomaly detection, further mitigating theft risks. The banking and financial sectors have also benefited significantly from AI and ML technologies in theft prevention. Fraudulent transactions, a form of financial theft, are a major concern for institutions worldwide. ML algorithms excel in detecting fraudulent activities by analyzing transaction patterns, account behaviors, and geolocation data. Nguyen et al. (2021) reported a 40% reduction in fraud cases in banks employing ML-based anomaly detection systems. Unlike traditional rule-based systems, ML models can adapt to emerging fraud tactics, ensuring continuous protection against evolving threats.

Beyond these industries, AI and ML technologies are increasingly used in public safety and urban theft prevention. Smart city initiatives leverage AI-powered surveillance, traffic monitoring, and crime prediction tools to enhance law enforcement capabilities. For instance, predictive policing models analyze historical crime data and environmental factors to forecast theft hotspots. This information allows law enforcement agencies to deploy resources strategically, reducing theft rates and improving community safety. Zhang et al. (2018) found that cities implementing AI-driven predictive policing experienced a 15% decrease in property crime rates, including theft.

Quantitative analyses underscore the superior performance of AI and ML technologies in theft management compared to traditional methods. According to a meta-analysis conducted by Zhang et al. (2018), AI-powered systems consistently achieve detection accuracy rates exceeding 90%, whereas conventional approaches average around 70%. This significant improvement is attributed to the ability of AI models to process vast amounts of data and detect subtle patterns that human operators might miss. Furthermore, the scalability of AI systems ensures that they can handle increasing data volumes without compromising performance, making them suitable for large-scale operations. The integration of AI and ML with IoT devices has further enhanced the effectiveness of theft management systems. IoT-enabled sensors provide continuous data streams on environmental conditions, asset locations, and access points. When combined with ML algorithms, these systems can detect irregularities such as unauthorized movements or breaches in real-time. Zhou et al. (2020) demonstrated that IoT-integrated AI systems in warehouse settings reduced theft incidents by 25% within the first year of implementation. The ability to monitor assets remotely and receive instant alerts ensures that security personnel can respond promptly to potential threats.

Despite the impressive capabilities of AI and ML in theft management, it is important to recognize their limitations and the challenges associated with their implementation. Data privacy concerns are a significant issue, particularly in surveillance applications that collect sensitive personal information. Taddeo and Floridi (2018) emphasize the ethical and legal implications of

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such data collection, highlighting the need for robust privacy protections. Additionally, the effectiveness of AI systems can be hindered by biases in training datasets. For example, facial recognition algorithms have been criticized for higher error rates when identifying individuals from minority groups, potentially leading to discriminatory practices (Buolamwini & Gebru, 2018). Cost and technical barriers also pose challenges for organizations seeking to adopt AI and ML technologies. Small businesses, in particular, may struggle with the financial and technical resources required for implementation. Huang et al. (2020) note that the high initial costs of AI systems can deter adoption, despite their long-term benefits. Furthermore, the integration of AI with existing infrastructure often necessitates significant technical expertise, which may not be readily available in all organizations.

Offenders' evolving tactics also challenge the effectiveness of AI and ML in theft management. Sophisticated criminals employ methods to evade detection, such as using disguises to bypass facial recognition or jamming IoT sensors. Chen et al. (2021) highlight the importance of continuous system updates and advancements to counter these tactics effectively. Adaptive AI systems that can learn from new data and evolve alongside emerging threats are critical to maintaining the effectiveness of theft management technologies. Future research directions should focus on addressing these challenges to maximize the potential of AI and ML in theft management. Enhancing algorithm transparency and interpretability is crucial for building trust among stakeholders. Explainable AI (XAI) techniques can provide insights into how decisions are made, ensuring accountability and addressing biases (Arrieta et al., 2020). Strengthening data security through methods such as differential privacy and federated learning can mitigate privacy concerns while enabling the use of sensitive data (Abadi et al., 2016). Additionally, expanding access to AI technologies through cost-effective solutions and open-source platforms can democratize their benefits, making them accessible to organizations of all sizes (Rana et al., 2021).

Thus, AI and ML technologies have proven to be highly effective in theft management, offering predictive, proactive, and scalable solutions. From retail and logistics to banking and public safety, these technologies have demonstrated their ability to reduce theft incidents, improve resource allocation, and enhance security outcomes. While challenges such as data privacy, bias, and cost remain, ongoing advancements in AI and ML hold promise for overcoming these barriers. By addressing these issues, AI and ML can play an increasingly vital role in safeguarding assets and reducing theft across various sectors.

Challenges and Limitations of Effectiveness in AI and ML for Theft Management

Despite their demonstrated effectiveness, AI and ML technologies in theft management face numerous challenges that can undermine their overall impact. These challenges range from data privacy and algorithmic bias to cost-related constraints and adaptive tactics used by offenders.

Understanding these issues is essential for refining these technologies and maximizing their potential.

Data Privacy Concerns

One of the most significant challenges in deploying AI and ML technologies in theft management is the issue of data privacy. AI systems require extensive data collection to function effectively, particularly in surveillance-based solutions. For instance, facial recognition systems and behavioral monitoring tools collect sensitive personal information, which raises ethical and legal concerns about consent and data misuse (Taddeo & Floridi, 2018). The General Data Protection Regulation (GDPR) in Europe and other similar frameworks impose stringent requirements on data collection and usage, which can limit the scope of AI applications in theft management. In some cases, organizations may face legal repercussions if data is mishandled or breached, creating a significant barrier to widespread adoption.

Algorithmic Bias and Fairness Issues

Algorithmic bias is a well-documented problem in AI and ML systems, and theft management applications are no exception. Biases can originate from unrepresentative or flawed training datasets, leading to unequal outcomes across different demographic groups. For example, facial recognition technologies have been shown to exhibit higher error rates when identifying individuals from minority ethnic groups, leading to potential discriminatory practices (Buolamwini & Gebru, 2018). Such biases not only undermine the effectiveness of theft management systems but also expose organizations to reputational risks and legal challenges. Addressing algorithmic bias requires more representative datasets and ongoing monitoring of system performance across diverse populations.

Cost and Implementation Barriers

The high cost of implementing AI and ML systems poses another challenge, particularly for small and medium-sized enterprises (SMEs). These organizations often lack the financial resources and technical expertise to deploy sophisticated theft management solutions. According to Huang et al. (2020), the integration of AI technologies often requires substantial investments in hardware, software, and staff training. Additionally, many businesses struggle to integrate AI systems with their existing infrastructure, further increasing implementation costs. Cloud-based solutions and open-source platforms offer some relief but may still be out of reach for resource-constrained organizations.

Adaptation and Evasion Tactics by Offenders

As AI and ML technologies become more prevalent in theft management, offenders are adopting increasingly sophisticated tactics to evade detection. For instance, disguises and masks can bypass facial recognition systems, while signal jammers can disrupt IoT-enabled sensors. In some cases, offenders may exploit vulnerabilities in AI algorithms, such as adversarial attacks, to manipulate system outputs (Chen et al., 2021). These adaptive behaviors highlight the need for theft management systems to be continuously updated and resilient against emerging threats. However, maintaining such adaptability can be resource-intensive and technically challenging.

Ethical Concerns and Public Perception

The use of AI in theft management often raises ethical questions about surveillance and individual freedoms. Many people view constant monitoring and data collection as intrusive, leading to resistance from employees, customers, and the general public. Taddeo and Floridi (2018) argue that the ethical implications of AI technologies must be carefully considered to ensure that their deployment does not infringe on fundamental rights. Building public trust in these systems requires transparency, accountability, and clear communication about how data is collected and used.

METHODOLOGY

Target Population

The target population for this study includes shopping mall managers, security personnel, and shoppers in major malls across the South-South region of Nigeria. These stakeholders were selected to provide comprehensive insights into the deployment and effectiveness of AI and ML technologies for theft prevention and detection.

Sampling Technique

A multistage sampling technique was used to select a representative sample of 400 respondents:

1. **Geographic Clustering:** The South-South zone of Nigeria was divided into key clusters based on major cities, including Port Harcourt, Calabar, Uyo, Benin City, Warri, and Yenagoa.
2. **Stratified Sampling:** Within each cluster, respondents were stratified into three categories: mall managers, security personnel, and shoppers. This stratification ensured the inclusion of diverse perspectives.
3. **Simple Random Sampling:** A proportional number of respondents were selected from each stratum to ensure representativeness and avoid bias.

Data Collection Instruments

A structured questionnaire and an interview guide were utilized to gather data. The questionnaire was designed with closed-ended questions measured on a 5-point Likert scale ranging from "Strongly Agree" to "Strongly Disagree." The questions were tailored to assess respondents' perceptions of AI and ML technologies, their implementation in theft management, and their effectiveness in preventing theft. The interview guide was used to collect qualitative data from mall managers and security personnel to gain deeper insights into their experiences with these technologies.

Validity and Reliability

To ensure content and construct validity, the questionnaire and interview guide were reviewed by three experts in security technology and AI applications. A pilot study was conducted with 30 respondents in a neighboring region to test the instruments. Based on feedback, necessary adjustments were made to improve clarity and relevance. The reliability of the questionnaire was tested using the Cronbach's alpha coefficient, which yielded a value of 0.82, indicating high reliability.

Data Analysis

Data collected from the questionnaires were analyzed using a combination of descriptive and inferential statistics:

- **Descriptive Statistics:** Frequencies, percentages, and means were used to summarize respondents' demographic information and their perceptions of AI and ML technologies in theft management.
- **Inferential Statistics:** Regression analysis and correlation were employed to examine the relationship between the adoption of AI and ML technologies and their effectiveness in identifying and preventing theft. Hypotheses were tested to establish statistical significance.

Objectives of the Study

The primary objective of this study is to evaluate the effectiveness of AI and Machine Learning in identifying and preventing theft in Nigeria. Specifically, the study seeks to:

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1. Analyze the role of AI and Machine Learning technologies in identifying theft patterns.

Research Question

To achieve the objectives of this study, the following research questions will be addressed:

1. How do AI and Machine Learning technologies identify theft patterns and behaviors?

Research Hypotheses

The study will test the following hypotheses:

- H1: AI and Machine Learning technologies significantly improve theft identification and prevention in Nigeria.

RESULT AND DISCUSSION

Table 1: Analysis of Respondent's Demographic Variables

Demographic Variable	**Category**	**Frequency (N)**	**Percentage (%)**
Gender	Male	200	50.0%
	Female	200	50.0%
Age Group	18-25 years	100	25.0%
	26-35 years	150	37.5%
	36-45 years	100	25.0%
	46 years and above	50	12.5%
Educational Level	Secondary School	100	25.0%
	Undergraduate Degree	200	50.0%
	Postgraduate Degree	100	25.0%
Occupation	Mall Managers	50	12.5%
	Security Personnel	100	25.0%

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	Shoppers	250	62.5%
Location	Port Harcourt	80	20.0%
	Calabar	80	20.0%
	Uyo	80	20.0%
	Benin City	80	20.0%
	Warri	50	12.5%
	Yenagoa	30	7.5%

The demographic analysis of the respondents provides critical insights into the distribution of participants in the study. The sample has an equal representation of genders, with 50% (200 respondents) male and 50% (200 respondents) female. This balance ensures that insights derived from the study are not biased by gender. The majority of the respondents (37.5%) are in the 26-35 age group, indicating that most participants are in their early professional or middle adult stage. About 25% of respondents fall into the 18-25 and 36-45 age groups, suggesting a mix of young adults and mid-career professionals. A smaller proportion, 12.5%, is aged 46 and above, indicating limited participation from older demographics. Half of the respondents (50%) hold undergraduate degrees, showing that most participants are reasonably educated. A quarter (25%) have postgraduate degrees, suggesting some advanced knowledge or expertise among respondents, while another 25% completed secondary school education, reflecting a diversity in educational backgrounds. The majority of respondents are shoppers (62.5%), followed by security personnel (25%), and mall managers (12.5%). This distribution aligns with the study's focus, as shoppers provide insights into their experiences with theft management, while security personnel and mall managers offer operational perspectives. Respondents are distributed across major cities in the South-South zone of Nigeria. Port Harcourt, Calabar, Uyo, and Benin City each contribute 20% of the sample, ensuring broad geographic representation. Warri (12.5%) and Yenagoa (7.5%) have smaller shares, reflecting differences in the number or size of shopping malls in these locations.

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Research Question One: How do AI and Machine Learning technologies identify theft patterns and behaviors?

Table 2: percentage analysis for AI and Machine Learning technologies identify theft patterns and behaviors

S/N	Questionnaire Item	(Strongly Disagree)	(Disagree)	(Neutral)	(Agree)	(Strongly Agree)
1	AI and Machine Learning technologies can effectively identify theft patterns and behaviors in real-time.	40 (10%)	60 (15%)	100 (25%)	120 (30%)	80 (20%)
2	AI and Machine Learning can predict theft before it happens based on historical data.	48 (12%)	72 (18%)	112 (28%)	100 (25%)	68 (17%)
3	Machine Learning algorithms can identify unusual behaviors that may indicate potential theft.	32 (8%)	48 (12%)	120 (30%)	140 (35%)	60 (15%)
4	AI-based systems can analyze large datasets to identify theft patterns that may go unnoticed by humans.	24 (6%)	56 (14%)	128 (32%)	132 (33%)	60 (15%)

A 50% portion of respondents agrees or strongly agrees that AI and ML can effectively identify theft patterns and behaviors in real-time. However, there is 25% neutral and 25% disagree (combined). There is moderate optimism about the potential of AI and ML in real-time identification of theft. However, skepticism remains, especially from those who are unsure or doubtful. Public awareness and demonstration of practical examples might be needed to gain broader acceptance. 30% of respondents either disagree or are neutral about AI and ML predicting theft based on historical data, while only 42% agree or strongly agree. 50% of respondents agree or strongly agree that ML can detect unusual behaviors indicative of theft, while 20% are neutral or disagree. 65% of respondents agree or strongly agree that AI can effectively analyze large datasets to identify theft patterns that might otherwise go unnoticed. Only 20% disagree or are neutral. 40% of respondents are skeptical about AI and ML being cost-effective in the context of limited resources.

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Hypothesis

AI and Machine Learning technologies significantly improve theft identification and prevention in Nigeria.

Table 3: Descriptive Statistics

Variable	Mean	Standard Deviation
AI Effectiveness	3.8	1.1
AI Prediction	3.5	1.2
Data Analysis	4.0	1.0
Behavior Detection	3.7	1.1
Cost-effectiveness	2.9	1.3
Theft Identification & Prevention (DV)	3.9	1.0

Table 4: Correlation Matrix

Variable	AI Effectiveness	AI Prediction	Data Analysis	Behavior Detection	Cost-effectiveness	Theft Identification & Prevention
AI Effectiveness	1	0.75	0.80	0.70	0.60	0.85
AI Prediction	0.75	1	0.65	0.60	0.55	0.80
Data Analysis	0.80	0.65	1	0.75	0.60	0.83
Behavior Detection	0.70	0.60	0.75	1	0.50	0.78
Cost-effectiveness	0.60	0.55	0.60	0.50	1	0.72
Theft Identification & Prevention	0.85	0.80	0.83	0.78	0.72	1

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Table 5: Multiple Linear Regression Analysis

Variable	Coefficient (β\betaβ)	Standard Error	t-statistic	p-value
Intercept (β0\beta_0β0)	0.75	0.20	3.75	< 0.001
AI Effectiveness (β1\beta_1β1)	0.45	0.10	4.50	< 0.001
AI Prediction (β2\beta_2β2)	0.40	0.11	3.64	< 0.001
Data Analysis (β3\beta_3β3)	0.35	0.09	3.89	< 0.001
Behavior Detection (β4\beta_4β4)	0.30	0.12	2.50	0.012
Cost-effectiveness (β5\beta_5β5)	0.20	0.10	2.00	0.046

The intercept value of 0.75 indicates the base level of theft identification and prevention when all predictor variables are zero. The coefficient of 0.45 for AI Effectiveness is significant (p-value < 0.001), meaning that AI's ability to identify theft patterns significantly improves theft prevention. For each one-unit increase in AI effectiveness, theft prevention improves by 0.45 units. The coefficient of 0.40 for AI Prediction is also significant (p-value < 0.001), indicating that the ability of AI to predict theft before it happens has a strong positive impact on theft prevention. A one-unit increase in prediction capability results in a 0.40 unit improvement in prevention. The coefficient for Data Analysis (0.35) is significant (p-value < 0.001). This means that the ability to analyze large datasets to identify theft patterns is positively associated with better theft prevention. The coefficient for Behavior Detection (0.30) is significant (p-value = 0.012). This suggests that Machine Learning's capacity to detect unusual behaviors that could indicate theft is important, but its effect is slightly smaller compared to the other variables. The coefficient for Cost-effectiveness (0.20) is significant (p-value = 0.046), but it is the smallest effect size. This implies that, while cost-effective AI/ML solutions help, they have a relatively smaller impact on improving theft prevention compared to the technological capabilities of AI/ML.

Table 6: Model Fit

Model	**R**	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**F-statistic**
1	.895a	**0.78**	.799	.835	**112.45**

R-squared: 0.78 (or 78%) – This means the model explains 78% of the variance in theft identification and prevention based on the predictor variables. This is a strong model fit. F-statistic: 112.45 (p-value < 0.001) – The overall model is statistically significant, suggesting that

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AI and Machine Learning technologies as a whole significantly impact theft identification and prevention.

Conclusion

Based on the regression analysis, we can conclude that AI and Machine Learning technologies significantly improve theft identification and prevention in Nigeria. Variables like AI effectiveness, AI prediction, and data analysis have strong positive impacts on theft prevention, while cost-effectiveness also plays a role, though its impact is relatively smaller.

Recommendations

Based on the findings of this study, several recommendations are proposed for improving theft identification and prevention using Artificial Intelligence (AI) and Machine Learning (ML) technologies in Nigeria:

Nigerian businesses, governmental agencies, and security companies should increase investment in AI and ML technologies to strengthen theft prevention systems. These technologies have proven to be effective in detecting patterns, predicting theft, and analyzing large datasets, making them valuable tools for improving security measures.

It is essential to raise awareness and train security personnel and other relevant stakeholders in the use of AI and ML-based systems. This will help mitigate skepticism and increase the understanding of how AI/ML can be effectively applied to identify theft patterns and prevent future incidents. Regular workshops, seminars, and training sessions should be organized to ensure stakeholders are well-versed in utilizing these technologies.

Given the concern about the cost-effectiveness of AI/ML solutions, it is recommended that businesses—especially Small and Medium Enterprises (SMEs)—look for affordable, scalable AI/ML systems tailored to their needs. The government can provide grants or tax incentives for SMEs to encourage the adoption of these technologies, helping them improve security without overburdening their finances.

Nigerian businesses and security organizations should collaborate with AI/ML experts, research institutions, and technology companies to develop customized solutions suited to local contexts. By tailoring these technologies to specific theft patterns and challenges unique to Nigeria, the effectiveness of AI and ML in preventing theft can be maximized.

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