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Risk Assessment of AI and Recommender Systems in Social Commerce: A Case Study of SMEs Leveraging Social Media

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Abstract - **This study investigates the application of artificial intelligence (AI) and recommender systems for risk assessment and management in small and medium-sized enterprises (SMEs) across social platforms such as WhatsApp Business. It evaluates the accuracy, usability, and impact of AI on risk profiling, management, and user engagement in online retail and social commerce. A quantitative survey was conducted with 200 SME participants to assess the performance of the AI tool. Results indicate that 56.5% of participants rated the tool as "more accurate," while 23% rated it as "highly accurate" compared to traditional techniques. Usability received high ratings, with 60.3% of respondents rating it as "very good," and 49.7% indicating they would recommend it. Notably, female and younger users reported higher levels of satisfaction and trust, potentially reflecting demographic differences in technology adoption. Furthermore, 85% of participants were unaware of AI tools for risk management, highlighting a significant knowledge gap. This study underscores the need for increased awareness, simplicity, and accessibility of AI solutions tailored to SMEs. The predictive model demonstrated a high level of effectiveness, with a Nagelkerke R^2 value of 0.871. Future recommendations include integrating chatbot applications, enabling offline functionality, and improving navigation to enhance trust and user acceptance. These enhancements could support the effective integration of AI into the digital economy, benefiting SMEs and offering implications for developers, policymakers, and business owners.**
***Keywords*: Artificial Intelligence (AI), Small and Medium-Sized Enterprises (SMEs), Risk Management, Recommender Systems, Social**

I. INTRODUCTION

Digitization involves the use of technologies to enhance productivity, transform business models, and improve interactions between consumers and businesses. It is a broad concept with many facets. Retailing is the second-largest employment provider after agriculture (Kumar, 2019). Traditional retail markets involve the sale of goods and services through physical stores. The emergence of digitization in retail has led to a significant shift from traditional retail markets to e-commerce. E-commerce refers to the process of purchasing goods through websites, online stores, or brand-specific applications. In contrast, social commerce (S-commerce) involves the direct sale of products and services through social media platforms (Asanprakit & Kraiwanit, 2023). Social commerce is a subset of e-commerce that focuses on strengthening user relationships to foster loyalty (Dincer & Dincer, 2023).

There are three pillars of social commerce: e-commerce, Web 2.0, and social networking sites (SNS), which enhance the online shopping experience (Huang & Benyoucef, 2013). It is considered part of e-commerce (Algharabat & Rana, 2021). However, social commerce offers advantages over traditional e-commerce, particularly in providing additional decision-making support prior to purchases. In 2022, the global social commerce market was valued at an estimated $992.4 billion. In Vietnam, 57% of purchases in 2021 occurred through social commerce-exceeding those made through traditional e-commerce platforms and websites (Hong & Ahn, 2024).

One important factor influencing customer satisfaction is the ease of shopping, which is facilitated by e-commerce (Samad *et al.,* 2023). S-commerce has transformed traditional business models by helping consumers make more informed purchasing decisions based on shared information and user experiences. Customer perception plays a crucial role in business success, with higher satisfaction increasing the likelihood of repeat purchases and customer loyalty (Kumar, 2019). The internet has significantly contributed to the growth of online businesses worldwide, emphasizing the need for further research in this area.

Despite the success of S-commerce and e-commerce, several challenges persist. These include data protection concerns, privacy issues, customs delays, ambiguous return processes, pricing and delivery transparency issues, and limited flexibility in delivery times and locations. As a result, not all firms have equal opportunities to participate in e-commerce (Ahi *et al.,* 2023). The success of e-commerce also depends on supportive government policies. In countries like Nigeria, underdeveloped formal institutions exacerbate the risks and limitations of e-commerce. SMEs in Nigeria face exogenous challenges such as poor infrastructure and limited loan accessibility, as well as endogenous challenges including weak corporate governance, poor management and accounting practices, limited business alliances, low levels of human capital development, and slow technological adoption. SMEs play a vital role in global economies by generating employment and contributing to gross domestic product (GDP).

However, they often lag behind larger firms in e-commerce adoption. Moreover, a significant gap exists between developed and less-developed countries in this regard. Although social commerce has attracted increasing research attention, gaps remain in areas such as social support, social presence, flow, trust, and customer engagement. Trust is one of the most critical factors influencing consumer purchasing decisions (Claudia *et al.,* 2018). Unlike structured e-commerce transactions, social commerce involves greater risk, as products purchased online are intangible and more vulnerable to fraud and scams (Dudi *et al.,* 2022).

Buyers attempt to establish trust by accessing seller and product information through platform features and user interactions (Mochamad & Shinta, 2022). However, sellers cannot control all user-generated content, making it difficult to build initial trust and sustain customer loyalty on social platforms. Consequently, some consumers still prefer purchasing certain products in physical stores (Chitra & Gopinath, 2021).

Artificial intelligence (AI) enables computers and software systems to perform tasks requiring human-like intelligence. Advances in information and communication technology (ICT) have driven continuous improvements in AI applications across various domains, including natural language processing, healthcare, retail, robotics, gaming, autonomous vehicles, facial recognition, law, finance, education, social media, and chatbots (Sain *et al.,* 2024). One emerging research area is the application of AI in e-commerce. AI and recommender systems have garnered substantial research attention for their roles in enhancing user experience and supporting decision-making (Valencia-Arias *et al.,* 2024).

Businesses use AI to personalize advertisements, create customized websites, automate content generation, and implement AI-powered chatbots. China's online retail market presents a compelling example of AI-driven e-commerce, with transactions reaching 9 trillion yuan and reflecting a 7.3% expansion in 2017 (Areiqat *et al.,* 2021). However, AI adoption in S-commerce remains limited.

Future AI applications in S-commerce may include AI-powered chatbots integrated with Facebook Messenger and WhatsApp, AI-driven content creation, AI-enabled visual search, cybersecurity enhancements, sales process automation, and personalized advertising.

Social media platforms allow users to share content such as images, videos, and text, and they have significantly influenced SMEs. The COVID-19 pandemic accelerated online shopping, further highlighting the importance of social media for SME business operations (Alam *et al.,* 2023; Belás *et al.,* 2021). In Indonesia, 54.66% of SMEs adopted social media during and after the pandemic to leverage broad networks and rapid information sharing (Rochmatullah *et al.,* 2022). Similarly, in Nigeria, platforms such as Instagram (7.1 million users), Facebook Messenger (3.5 million users), LinkedIn (7.5 million members), Snapchat (12.35 million users), and Twitter (4.95 million users) have become vital to business transactions (Akeusola, 2023). Nigeria's social commerce industry is projected to grow by 43.3% annually, reaching \$1.19 billion in 2022 and \$5.04 billion by 2028. PR Newswire predicts global social commerce will grow by 82.4% annually, reaching \$1,003.8 million in 2022, with a projected compound annual growth rate (CAGR) of 71.3% between 2022 and 2028.

Various e-commerce models exist, including business-to-business (B2B), business-to-consumer (B2C), and consumer-to-consumer (C2C) platforms. These models generate large volumes of data, often resulting in information overload. Many businesses address this issue through recommender systems, which provide personalized product suggestions to enhance user satisfaction. These systems are classified as software tools that suggest products based on user preferences, thereby supporting decision-making. They are widely used in decision support systems (DSS), information retrieval (IR), and machine learning (ML). However, a significant gap remains in AI-based recommender systems tailored for SMEs operating on social commerce platforms such as WhatsApp Business and Facebook Marketplace.

This study aims to develop a mobile recommender system for SME businesses, evaluate its accuracy and effectiveness in risk identification and profiling within S-commerce, and assess the potential impact of AI applications on risk assessment and management in online retail and social commerce. The findings will contribute to the adoption of AI in S-commerce by SMEs, enhancing their competitiveness in the digital economy.

II. AIM AND OBJECTIVES OF THE STUDY

The focus of this study is the risk assessment involved in the use of recommended systems by small and medium-sized enterprises (SMEs). The aim of this research is to bridge the gap between the adoption of recommended systems by SMEs and customers' confidence in using artificial intelligence (AI) in SME businesses.

The objectives of this study are to:

1. Assess the accuracy and effectiveness of the AI application in identifying and profiling risks.

2. Evaluate the usability and user experience of the application.
3. Explore the potential impact of the AI application on risk assessment and management within the online retail and social commerce domains.

Research Questions:

1. How accurate and effective is the AI application in identifying and profiling risks for small and medium-sized enterprises (SMEs)?
2. What is the level of usability and user experience provided by the AI application?
3. What is the potential impact of the AI application on risk assessment and management within the online retail and social commerce domains?

III. REVIEW OF LITERATURE

Artificial intelligence (AI) technology has proven beneficial in various ways. AI assistants, such as chatbots, enhance customer experience by responding to inquiries, complaints, and requests in real time using natural language processing (NLP). For example, Shopping Xiaomi, launched in 2017 by Alibaba for Taobao merchants, utilizes AI to improve customer interactions. AI is also applied in intelligent logistics to optimize smart supply chains. Companies such as IBM, Alibaba, and JD have implemented automated systems for supply chain and logistics management (Song *et al.,* 2019).

Furthermore, AI can evaluate market dynamics and address the challenge of optimal pricing. It also plays a critical role in fraud detection and prevention, with machine learning (ML) algorithms analyzing past fraudulent activities to predict potential fraud cases. Many e-commerce companies use AI for personalized recommendations by analyzing customer behavior, purchase history, and search patterns (Lissy *et al.,* 2024). Baidu, for instance, employs an intelligent recommendation system capable of managing complex scenarios involving diverse users, regions, time periods, and merchants. This system enhances user engagement and drives business growth. A prominent example of social commerce (S-commerce) is Xiaohongshu, a platform that caters to young urban women.

It features user-generated content, including product reviews, lifestyle tips, and shopping experiences, allowing users to discover and share high-quality domestic and international products. AI supports personalized recommendations based on user behavior, product recognition for streamlined shopping, and content moderation using NLP and ML. These AI-driven capabilities improve user experience, increase conversion rates, and optimize platform operations. Xiaohongshu continuously refines its strategy to align with evolving user needs and preferences (Kang *et al.,* 2024).

A. Recommendation System Algorithms

Several algorithms are used in recommender systems (RSs), including the following:

1. *Collaborative Recommender Systems:* These systems suggest products based on user preferences, leveraging the collective wisdom of the community to predict individual interests. They are classified into user-based and item-based collaborative filtering (CF).
2. *Content-Based Recommender Systems:* These systems recommend products based on item similarity, predicting user interest by analyzing previously liked items.
3. *Demographic-Based Recommender Systems:* These systems consider factors such as age, gender, and location to tailor recommendations.
4. *Community-Based Recommender Systems:* These systems utilize collective user feedback to improve recommendation quality.
5. *Hybrid Recommender Systems:* These systems combine multiple recommendation algorithms to enhance accuracy and performance.

Khan *et al.,* (2021) addressed issues of data sparsity and contextual understanding by proposing a hybrid contextual recommender system (RS) that integrates Word2Vec for semantic comprehension and convolutional neural networks (CNNs) for contextual analysis. Their model, incorporated into Probabilistic Matrix Factorization (PMF), outperformed traditional RSs, although challenges related to scalability and real-time application remain.

Xu and Sang (2022) developed an integrated recommendation model combining Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and eXtreme Gradient Boosting (XGBoost), tested on real-world e-commerce datasets. Their approach offers a scalable and effective solution for enhancing user experience.

Loukili *et al.,* (2023) addressed information overload using an association rule-based approach with the Frequent Pattern Growth (FP-Growth) algorithm to analyze transactional data and generate personalized product recommendations. Their study demonstrated that the system reduces data overload, increases user engagement, and boosts e-commerce performance.

Similarly, Salampasis *et al.,* (2023) explored next-item, next-basket, and purchase intent prediction using long short-term memory (LSTM) networks, graph-based methods, and embedding models (Item2Vec, Doc2Vec). Their findings indicated that LSTM performed best for next-item prediction, while graph-based methods offered a balance between efficiency and effectiveness.

Padhy *et al.,* (2024) improved product recommendation accuracy by integrating Apriori, FP-Growth, and collaborative filtering to analyze interaction data. Their approach achieved 81% accuracy, surpassing individual algorithms in scalability and efficiency while addressing challenges such as the cold-start problem and sparse data.

B. Challenges in Recommender Systems

While recommender systems (RSs) enhance user satisfaction, they also face several challenges, including:

1. Data sparsity: Occurs when users provide insufficient ratings, resulting in limited data availability.
2. Cold-start problem: Arises when new users or items are introduced without adequate historical data.
3. Scalability issues: Become prominent when handling large datasets, requiring efficient computational resources.
4. Privacy concerns: As RSs rely on extensive user data for accurate predictions, implementing strong data protection measures is essential.
5. Robustness: RSs must be resilient to shilling attacks or profile injection attacks that aim to manipulate recommendation outcomes (Kumar & Sharma, 2016).

Fig. 1 (below) illustrates the various challenges affecting recommender systems (RSs) and their corresponding impact percentages.

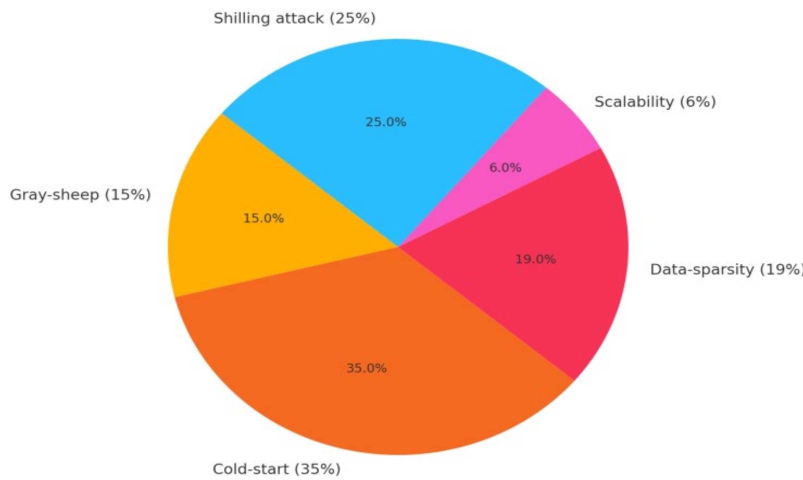

Fig.1 Challenges in Recommender Systems

Žigienė *et al.,* (2019) examined commercial risk management through artificial intelligence (AI) and machine learning (ML). The study developed a conceptual framework that incorporates data sharing among supply chain participants and AI-based risk prediction models. The results highlight AI's significance in risk identification, management, and assessment, leading to improved resource allocation and decision-making for small and medium-sized enterprises (SMEs).

Xu *et al.,* (2024) investigated AI applications in the financial sector by integrating ML, deep learning (DL), and natural language processing (NLP) to assess AI's role in risk detection, compliance, and fraud prevention. The findings indicate a 20% improvement in credit risk prediction accuracy, a 30% increase in anomaly detection speed, and a 60% reduction in false positives for fraud detection-demonstrating AI's effectiveness. By 2028, AI is projected to reduce financial risk-related losses by 25% and enhance operational efficiency by 35%. Biolcheva (2021) combined ML, DL, semantic analysis, and predictive analytics with expert insights to estimate risk in dynamic business environments. The study validated risk assessment models using probability matrices and Monte Carlo simulations, enhancing the precision of risk quantification. Additionally, the research emphasizes investing in AI systems and fostering collaborations between AI developers and risk management professionals.

Božić (2023) applied AI to integrated risk management, leveraging ML, NLP, and predictive analytics to improve risk identification, patient safety, and operational efficiency. However, the study noted challenges related to data bias, AI model interpretability, and implementation complexity.

Polemi *et al.,* (2024) examined uncertainties in AI trustworthiness and introduced several AI risk managements frameworks-such as S.A.F.E. and T.R.U.S.T.-designed to assess and mitigate AI-related risks, drawing on insights from NIST, ENISA, and ISO. The study concludes that ensuring AI trustworthiness requires collaboration among cybersecurity experts, AI developers, and social science researchers, integrating technical, ethical, and behavioral insights to enhance AI's robustness, transparency, and societal acceptance.

C. Recommendation Systems and SME Performance

The numerous advantages of recommendation systems (RSs) have contributed to improved business performance. SMEs play a crucial role in economic growth and development by driving exports and generating employment. In Indonesia, SMEs constitute 64.3 million business units, accounting for 61.9% of the GDP and 97%

of the national workforce. However, SMEs face challenges in adopting AI and digital technologies due to limited financial resources, marketing constraints, productivity issues, and competitive pressures (Nazaruddin *et al.,* 2024). The role of digital marketing and social media in SME performance is significant.

The Diffusion of Innovation Theory explains how technological adoption is facilitated by digital marketing interventions that enhance SME efficiency. Jaini *et al.,* (2024) identified three key digital marketing tools-website interaction, social media, and e-commerce-that improve SME capabilities. A study conducted in the Wakiso District, Uganda, highlights the widespread use of WhatsApp for customer engagement, product marketing, and order processing. The findings reveal that WhatsApp usage contributed to a 20.6% improvement in SME performance (Richard *et al.,* 2023). However, despite its benefits, few studies have explored the integration of AI and RSs within platforms like WhatsApp to enhance SME operations. Although several AI risk management frameworks exist across various domains, research on the application of RSs and AI-driven risk management in e-commerce remains limited. Further studies are needed to address these gaps and explore AI's potential in SME risk assessment and recommendation systems.

IV. METHODOLOGY

A. Research Design

This study employed a quantitative research approach using correlational survey design, focusing on numerical data and statistical analysis.

B. Data Collection

Data were collected using online questionnaires distributed to over 200 participants. However, complete responses were obtained from 200 participants.

C. Sampling Technique

The study adopted a non-probability sampling method, specifically purposive sampling. This technique was chosen because the questionnaire targeted SME business owners with online shopping experience.

D. Sample Description

Participants included business owners from various sectors, such as fashion, social media, information technology (IT), and entrepreneurship. They were invited to use the AI application and complete the online questionnaire based on their interaction with the system.

E. Tools and Techniques

A content-based filtering algorithm was employed to capture users' perspectives on vendors. Users rated vendors based on their experience, as content-based recommender systems rely on user metadata to generate personalized recommendations.

The technologies used in this study included:

1. C# (.NET Framework): A versatile programming language used with Xamarin for building cross-platform mobile applications.
2. MSSQL: A relational database management system used to store, retrieve, and manage application data for each registered participant.
3. AWS Simple Email Service (SES): An email service used for transactional messages, such as account confirmation, password resets, and order confirmations.
4. AWS S3 Bucket: A scalable storage solution for managing media files and other data.

F. Method of Data Analysis

1. Data was analyzed using IBM SPSS Statistics 25.
2. Demographic characteristics of respondents were analyzed using simple percentages.
3. Research questions and hypotheses were tested using the ordinal regression model.

G. Ethical Considerations

Ethical considerations included obtaining informed consent and ensuring participant confidentiality and anonymity.

H. Limitations

Some limitations of this research include the constrained sample size and limited generalizability. Future studies could address these limitations by expanding the sample size and exploring broader generalization.

I. Results and Discussion

Fig.2 and Fig.3 show the sign-up and login interfaces, respectively, while Fig.4 displays the landing/welcome page for the recommender system application. Enrolling vendors and customers on this platform are straightforward, requiring only a phone number and password. Figure 5 shows the vendor ranking page, where vendors can be ranked, and their trust scores viewed by customers.

J. Mobile App Design

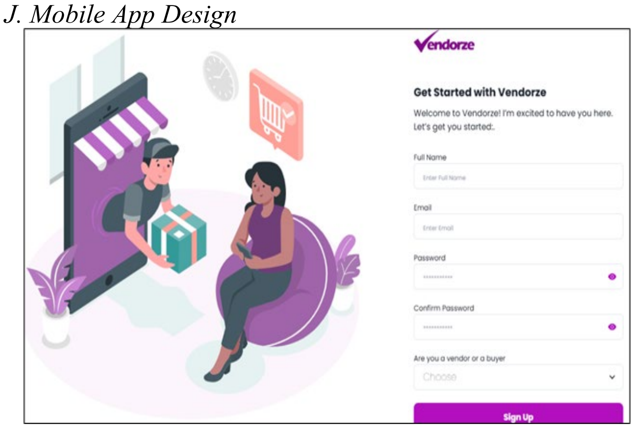

Fig.2 Sign Up Page

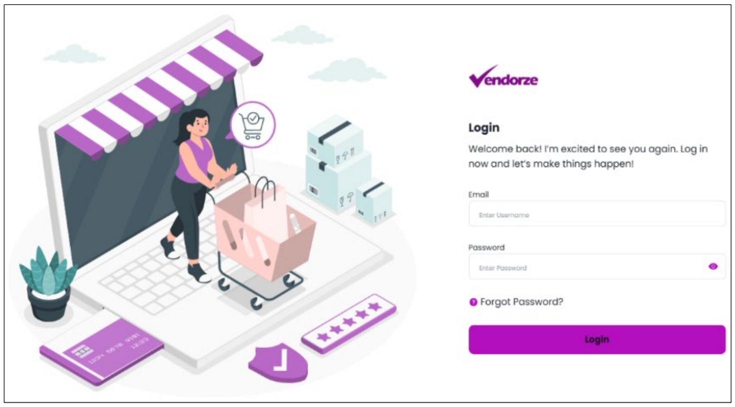

Fig.3 Login Page

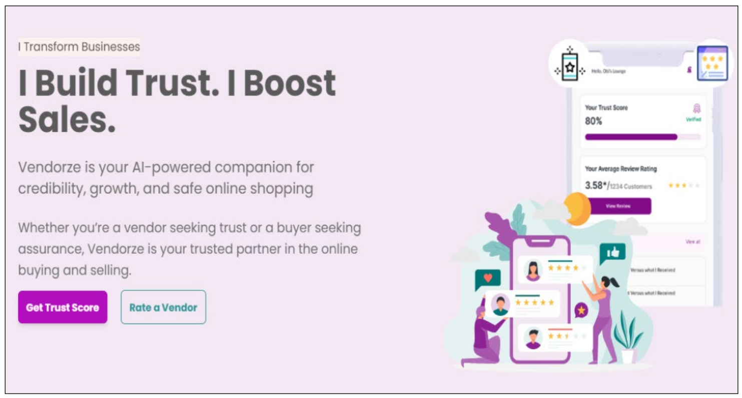

Fig.4 Landing Page

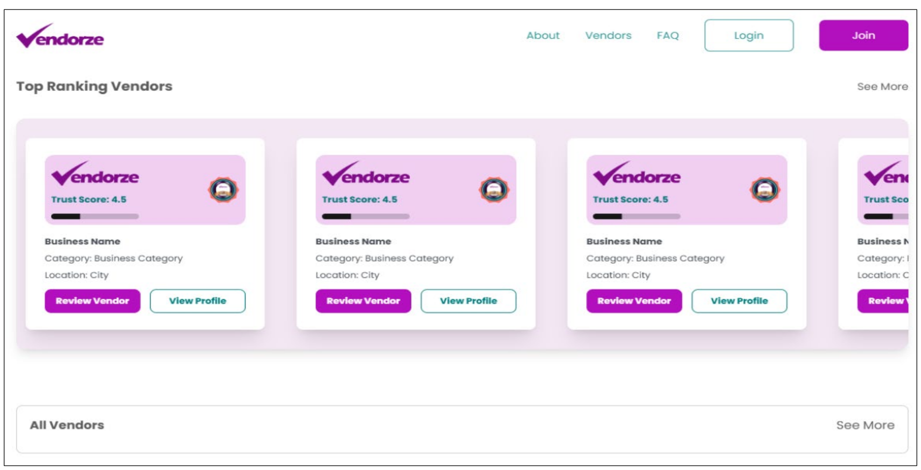

Fig.5 Vendor Ranking Page

K. Data Analysis

Objective 1: To assess the accuracy and effectiveness of the AI application in identifying and profiling risks.

Research Question 1: How accurate and effective is the AI application in identifying and profiling risks for small and medium-sized enterprises (SMEs)?

TABLE I MODEL FITTING INFORMATION WAS USED TO ASSESS THE ACCURACY AND EFFECTIVENESS OF THE AI APPLICATION IN IDENTIFYING AND PROFILING RISKS

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	440.690	0	0	0
Final	122.724	317.966	113	.000

Link function: Logit

Table I presents the model fitting information used to assess the accuracy and effectiveness of the AI application in identifying and profiling risks. The significant reduction in the -2 Log Likelihood value from 440.690 (intercept-only model) to 122.724 (final model) indicates an improved fit when predictors are included. The chi-square value of 317.966, with 113 degrees of freedom and a p-value of .000, confirms that the final model provides a significantly better fit than the intercept-only model.

TABLE II GOODNESS-OF-FIT AND PSEUDO R-SQUARE VALUES WERE USED TO ASSESS THE ACCURACY AND EFFECTIVENESS OF THE AI APPLICATION IN IDENTIFYING AND PROFILING RISKS

	Chi-Square	**df**	**Sig.**	**Pseudo R-Square**	
Pearson	1297.997	655	0.000	Cox and Snell	0.796
Deviance	122.724	655	1.000	Nagelkerke	0.895
				McFadden	0.722

Link function: Logit

Table II presents the goodness-of-fit and pseudo-R-square measures for evaluating the AI application's accuracy and effectiveness in identifying and profiling risks. The Pearson chi-square value (1,297.997, $p < .001$) indicates a significant deviation from a perfect fit, whereas the deviance statistic (122.724, $p = 1.000$) suggests that the model fits the data well. The high pseudo-R-square values-Cox and Snell = 0.796, Nagelkerke = 0.895, and McFadden = 0.722-indicate that a substantial proportion of the variance in the dependent variable is explained by the model. These results highlight the strong predictive power and overall effectiveness of the AI model. The parameter estimates in Table III provide insights into the factors influencing the perceived accuracy and effectiveness of the AI application in identifying and profiling risks.

The threshold values for perceived AI accuracy levels are not statistically significant, as all p-values exceed 0.05, indicating that variations in perceived accuracy levels are not strongly associated with significant thresholds.

TABLE III PARAMETER ESTIMATES WERE USED TO EVALUATE THE ACCURACY AND EFFECTIVENESS OF THE AI APPLICATION IN IDENTIFYING AND PROFILING RISKS

Parameter	**Estimate**	**Std. Error**	**Wald**	**df**	**Sig.**	**95% Confidence Interval**
Threshold						
[Perceived AI accuracy = 1]	-12.124	9.981	1.475	1	0.224	[-31.687, 7.439]
[Perceived AI accuracy = 2]	-6.728	9.906	0.461	1	0.497	[-26.143, 12.688]
[Perceived AI accuracy = 3]	-0.501	9.998	0.003	1	0.96	[-20.098, 19.095]
[Perceived AI accuracy = 4]	8.863	9.789	0.82	1	0.365	[-10.322, 28.048]
Location						
[Acceptability of AI in fraud detection]	1.745	0.592	8.676	1	0.003	[0.584, 2.906]
[Industry = Private Sector]	2.659	5.055	0.277	1	0.599	[-7.248, 12.567]
[Industry = Fashion]	30.512	-	-	1	-	[30.512, 30.512]
[Industry = Civil Service]	4.204	5.333	0.621	1	0.431	[-6.249, 14.656]
[Industry = Dropshipping]	2.395	5.505	0.189	1	0.664	[-8.395, 13.185]
[Industry = Education]	9.120	5.291	2.971	1	0.085	[-1.250, 19.489]
[Industry = Agriculture]	-1.879	5.914	0.101	1	0.751	[-13.470, 9.711]
[Industry = Banking/Finance]	29.202	8088.934	0.000	1	0.997	[-15824.818, 15883.222]
[Industry = Health sector]]	26.246	12789.728	0.000	1	0.998	[-25041.161, 25093.652]
[Industry = Construction]	28.617	12789.726	0.000	1	0.998	[-25038.785, 25096.018]
[Industry = IT, ICT and Tech]	5.304	5.669	0.875	1	0.350	[-5.808, 16.415]
[Industry = Marketing]	23.123	12789.730	0.000	1	0.999	[-25044.287, 25090.533]
[Industry = Textile]	5.415	5.173	1.096	1	0.295	[-4.725, 15.554]
[Industry = Trading]	13.063	5.625	5.392	1	0.020	[2.037, 24.088]

[Industry = None]	8.961	5.482	2.672	1	0.102	[-1.783, 19.706]
[Industry = Others]	0[a]	-	-	0	-	-
Gender						
[Gender = Female]	-1.269	0.988	1.648	1	0.199	[-3.206, 0.668]
[Gender = Male]	0a	-	-	0	-	-
Marital Status						
[Marital Status = Married]	-2.251	1.131	3.965	1	0.046	[-4.468, -0.035]
[Marital Status = Divorced]	-2.576	1.598	2.598	1	0.107	[-5.709, 0.557]
[Marital Status = Single]	0[a]	-	-	0	-	-
Highest Educational Qualification						
[HEQ = B.Sc./HND]	-8.740	3.887	5.055	1	0.025	[-16.358, -1.121]
[HEQ = ND/NCE]	-11.204	4.099	7.471	1	0.006	[-19.238, -3.170]
[HEQ = Postgraduate Degree]	-6.016	3.992	2.271	1	0.132	[-13.841, 1.808]
[HEQ = Secondary School Certificate]	0[a]	-	-	0	-	-
Employment Status						
[ES = Employed]	.384	1.153	0.111	1	0.739	[-1.877, 2.645]
[ES = Self-Employed]	-.321	1.351	0.057	1	0.812	[-2.968, 2.326]
[ES = Unemployed]	0[a]	-	-	0	-	-
Age						
[Age = 21-30 years]	9.908	3.655	7.350	1	0.007	[2.745, 17.071]
[Age = 31-40 years]	9.095	3.689	6.079	1	0.014	[1.865, 16.324]
[Age = 41 years and above]	9.811	4.161	5.559	1	0.018	[1.655, 17.967]
[Age = Under 21 years]	0[a]	-	-	0	-	-
Years in Business						
[YB = 1-2 Years]	8.767	4.836	3.286	1	0.070	[-0.711, 18.245]
[YB = 3-5 Years]	9.256	4.891	3.582	1	0.058	[-0.329, 18.841]
[YB = 6-9 Years]	5.242	5.017	1.092	1	0.296	[-4.591, 15.075]
[YB = Just Started]	10.202	5.517	3.419	1	0.064	[-0.612, 21.015]
[YB = More than 10 Years]	0[a]	-	-	0	-	-
Occupation						
[Occupation = Business]	-9.121	5.877	2.409	1	0.121	[-20.640, 2.397]
[Occupation = Civil Servant]	-8.687	6.224	1.948	1	0.163	[-20.885, 3.511]
[Occupation = Developer]	-7.718	7.700	1.005	1	0.316	[-22.809, 7.374]
[Occupation = Entrepreneur]	-15.517	6.838	5.149	1	0.023	[-28.919, -2.114]
[Occupation = Fashion]	-7.028	5.818	1.460	1	0.227	[-18.431, 4.374]
[Occupation = Social Media Manager]	-29.441	12789.729	.000	1	0.998	[-25096.850, 25037.968]
[Occupation = Student]	-17.470	6.733	6.732	1	0.009	[-30.666, -4.274]
[Occupation = Teaching]	-17.146	7.674	4.992	1	0.025	[-32.186, -2.106]
[Occupation = Others]	0[a]	-	-	0	-	-
Trust in AI for Fraud Detection						
[TAIFD = High]	-.671	1.196	0.315	1	0.575	[-3.015, 1.673]
[TAIFD = Low]	-4.905	7.865	0.389	1	0.533	[-20.321, 10.511]
[TAIFD = Moderate]	0[a]	-	-	0	-	-

AI's Effectiveness vs. Traditional Methods						
[AIETM = Equally Effective]	-7.445	1.933	14.836	1	0.000	[-11.233, -3.657]
[AIETM = Less Effective]	2.685	12789.728	.000	1	1.000	[-25064.721, 25070.091]
[AIETM = More Effective]	-4.125	1.348	9.362	1	0.002	[-6.767, -1.483]
[AIETM = Much More Effective]	0[a]	-	-	0	-	-
Frequency of Engagement in Online Retail/Social Commerce Activities						
[FESCA = Daily]	-2.259	1.464	2.381	1	0.123	[-5.129, 0.611]
[FESCA = Monthly]	0.719	0.895	0.646	1	0.422	[-1.035, 2.473]
[FESCA = Never]	31.033	12.760	5.915	1	0.015	[6.024, 56.042]
[FESCA = Rarely]	-2.572	1.297	3.928	1	0.047	[-5.115, -0.029]
[FESCA = Weekly]	0[a]	-	-	0	-	-
Role in Social Commerce						
[RSC = App Designer]	15.830	9906.879	0.000	1	0.999	[-19401.295, 19432.955]
[RSC = Both buyer and seller]	-.594	4.820	0.015	1	0.902	[-10.042, 8.853]
[RSC = Buyer]	-.213	1.293	0.027	1	0.869	[-2.747, 2.321]
[RSC = Platform Administrator]	-.528	2.107	0.063	1	0.802	[-4.659, 3.602]
[RSC = None]	-9.778	4.341	5.073	1	0.024	[-18.286, -1.269]
[RSC = Seller]	0[a]	-	-	0	-	-
Opinion in AI Systems Providing Explanations for their Decisions						
No	-0.284	1.288	0.049	1	0.826	[-2.808, 2.240]
Yes	0[a]	-	-	0	-	-
Believe in AI Effectiveness in Detecting and Preventing Fraud						
No	2.782	1.652	2.835	1	0.092	[-0.456, 6.020]
Yes	0[a]	-	-	0	-	-
Perceived Accuracy of AI in Identifying and Predicting Risks vs. Traditional Methods						
Equally accurate	-0.669	0.861	0.605	1	0.437	[-2.357, 1.018]
Less accurate	-7.429	6.862	1.172	1	0.279	[-20.878, 6.019]
More accurate	0[a]	-	-	0	-	-

However, the location variable-particularly acceptability of AI in fraud detection-is significant ($p = .003$), suggesting that higher acceptability is associated with improved perceived AI accuracy. Furthermore, industry-specific impacts reveal a notable effect in sectors such as trading ($p = .020$), while other industries, including education and civil service, show marginal or non-significant contributions. Regarding demographic and personal factors, marital status (married) and educational qualifications (B.Sc./HND and ND/NCE) significantly influence perceptions, with married individuals and those holding these qualifications reporting lower perceived accuracy. Age also plays a role, as older age groups (21-30, 31-40, and 41+ years) show significant positive associations ($p < .05$) compared to those under 21. Occupation further highlights differences, with entrepreneurs, students, and teachers reporting significantly lower perceived AI accuracy than other occupational groups. Lastly, attitudes toward AI's effectiveness compared to traditional methods indicate that users who perceive AI as equally or more effective exhibit significantly different perceptions ($p < .05$), underscoring the importance of trust and effectiveness in shaping user perspectives.

Objective 2: To evaluate the usability and user experience of the AI application.

Research Question 2: What is the level of usability and user experience provided by the AI application?

TABLE IV MODEL FITTING INFORMATION FOR EVALUATING THE USABILITY AND USER EXPERIENCE OF THE AI APPLICATION

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	409.920			
Final	114.004	295.916	106	.000

Link function: Logit

Table IV indicates that the inclusion of predictors significantly improves the model fit, as evidenced by the reduction in the -2 Log Likelihood value from 409.920 (intercept-only model) to 114.004 (final model), along with a significant chi-square value ($\chi^2 = 295.916$, $p < .001$). This suggests that the predictors meaningfully explain the variability in the usability and user experience of the application under the logit link function.

TABLE V GOODNESS-OF-FIT AND PSEUDO R-SQUARE MEASURES FOR EVALUATING THE USABILITY AND USER EXPERIENCE OF THE APPLICATION

	Chi-Square	df	Sig.	Pseudo R-Square	
Pearson	10355.887	470	0.000	Cox and Snell	0.774
Deviance	114.004	470	1.000	Nagelkerke	0.887
				McFadden	0.722

Link function: Logit

Table V presents the model fit and explanatory power for evaluating the usability and user experience of the application. The significant Pearson chi-square value ($\chi^2 = 10{,}355.887$, $p < .001$) indicates that the model captures substantial variability, although such a large chi-square value may also reflect potential issues such as model complexity or overdispersion. The pseudo-R-square values-particularly Nagelkerke's $R^2 = 0.887$-suggest that the model explains 88.7% of the variance in usability and user experience, demonstrating excellent predictive power. Additionally, the deviance chi-square value ($\chi^2 = 114.004$, $p = 1.000$) indicates that the model fits the data well under the logit link function.

TABLE VI PARAMETER ESTIMATES FOR EVALUATING THE USABILITY AND USER EXPERIENCE OF THE APPLICATION

Parameter	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval
Threshold						
[AI User-friendliness = 1]	1.424	11.299	0.016	1	0.900	[-20.721, 23.569]
[AI User-friendliness = 2]	6.899	11.261	0.375	1	0.540	[-15.171, 28.970]
[AI User-friendliness = 3]	16.154	11.426	1.999	1	0.157	[-6.241, 38.548]
Location						
[Acceptability of AI in fraud detection]	1.456	.634	5.281	1	0.022	[0.214, 2.699]
[Industry = Private Sector]	8.097	4.499	3.240	1	0.072	[-0.720, 16.914]
[Industry = Fashion]	5.180	5.210	0.988	1	0.320	[-5.032, 15.391]
[Industry = Civil Service]	8.245	4.858	2.880	1	0.090	[-1.277, 17.766]
[Industry = Dropshipping]	4.731	5.018	0.889	1	0.346	[-5.104, 14.567]
[Industry = Education]	-1.094	4.857	0.051	1	0.822	[-10.614, 8.425]
[Industry = Agriculture]	-1.669	5.027	0.110	1	0.740	[-11.521, 8.183]
[Industry = Banking/Finance]	7.128	5.808	1.506	1	0.220	[-4.254, 18.511]
[Industry = Health sector]]	32.053	13496.876	0.000	1	0.998	[-26421.338,26485.443]
[Industry = Construction]	-1.853	6.430	0.083	1	0.773	[-14.456, 10.750]
[Industry = ICT]	20.515	10.177	4.064	1	0.044	[0.569, 40.461]
[Industry = IT]	7.329	4.882	2.254	1	0.133	[-2.239, 16.897]
[Industry = Tech]	7.684	5.297	2.104	1	0.147	[-2.698, 18.067]
[Industry = Marketing]	34.818	13496.878	0.000	1	0.998	[-26418.576, 26488.213]
[Industry = Textile]	10.982	4.837	5.154	1	0.023	[1.501, 20.463]
[Industry = Trading]	8.759	4.771	3.370	1	0.066	[-.593, 18.111]
[Industry = None]	8.713	5.387	2.616	1	0.106	[-1.845, 19.272]
[Industry = Others]	0^a	-	-	0	-	-
Gender						
[Gender = Female]	2.126	.951	4.996	1	0.025	[0.262, 3.989]
[Gender = Male]	0a	-	-	0	-	-

Marital Status						
[Marital Status = Married]	-0.506	2.183	0.054	1	0.817	[-4.784, 3.773]
[Marital Status = Divorced]	2.403	1.133	4.498	1	0.034	[0.182, 4.623]
[Marital Status = Single]	0[a]	-	-	0	-	-
Highest Educational Qualification						
[HEQ = B.Sc./HND]	-1.471	2.395	0.377	1	0.539	[-6.166, 3.224]
[HEQ = ND/NCE]	-1.348	2.472	0.297	1	0.585	[-6.192, 3.496]
[HEQ = Postgraduate Degree]	0.347	2.799	0.015	1	0.901	[-5.138, 5.833]
[HEQ = Secondary School Certificate]	0[a]	-	-	0	-	-
Employment Status						
[ES = Employed]	-0.591	1.326	0.199	1	0.656	[-3.190, 2.008]
[ES = Self-Employed]	1.548	1.486	1.086	1	0.297	[-1.363, 4.460]
[ES = Unemployed]	0[a]	-	-	0	-	-
Age						
[Age = 21-30 years]	2.337	2.465	0.898	1	0.343	[-2.495, 7.169]
[Age = 31-40 years]	0.985	2.437	0.163	1	0.686	[-3.791, 5.760]
[Age = 41 years and above]	1.008	2.920	0.119	1	0.730	[-4.715, 6.731]
[Age = Under 21 years]	0[a]	-	-	0	-	-
Years in Business						
[YB = 1-2 Years]	8.849	4.858	3.318	1	0.069	[-0.672, 18.370]
[YB = 3-5 Years]	9.447	4.852	3.791	1	0.052	[-0.062, 18.957]
[YB = 6-9 Years]	9.306	5.047	3.399	1	0.065	[-0.587, 19.198]
[YB = Just Started]	13.246	5.452	5.903	1	0.015	[2.561, 23.931]
[YB = More than 10 Years]	0[a]	-	-	0	-	-
Occupation						
[Occupation = Business]	-8.806	8.468	1.081	1	0.298	[-25.402, 7.791]
[Occupation = Civil Servant]	-4.775	8.661	0.304	1	0.581	[-21.750, 12.199]
[Occupation = Developer]	-4.542	9.606	0.224	1	0.636	[-23.370, 14.286]
[Occupation = Entrepreneur]	-14.864	8.976	2.742	1	0.098	[-32.457, 2.729]
[Occupation = Fashion]	-9.355	8.490	1.214	1	0.270	[-25.994, 7.285]
[Occupation = Social Media Manager]	-36.396	13496.879	0.000	1	0.998	[-26489.792, 26417.001]
[Occupation = Student]	-9.273	8.867	1.094	1	0.296	[-26.653, 8.106]
[Occupation = Teaching]	-4.593	8.749	0.276	1	0.600	[-21.741, 12.556]
[Occupation = Front End Developer]	-25.824	10.475	6.078	1	0.014	[-46.355, -5.294]
[Occupation = Others]	0[a]	-	-	0	-	-
Opinion on Recommending the Application to others						
[ORAO = Likely]	-8.621	2.011	18.374	1	0.000	[-12.563, -4.679]
[ORAO = Neutral]	-9.581	2.186	19.211	1	0.000	[-13.865, 5.296]
[ORAO = Somewhat Likely]	-8.633	2.863	9.090	1	0.003	[-14.245, -3.021]
[ORAO = Very Likely]	0[a]	-	-	0	-	-
Frequency of Engagement in Online Social Commerce Activities						
[FESCA = Daily]	0.033	1.067	0.001	1	0.975	[-2.058, 2.123]
[FESCA = Monthly]	0.734	1.047	0.492	1	0.483	[-1.318, 2.786]
[FESCA = Never]	21.309	10.014	4.527	1	0.033	[1.681, 40.937]

[FESCA = Rarely]	-1.701	1.404	1.467	1	0.226	[-4.453, 1.051]
[FESCA = Weekly]	0[a]	-	-	0	-	-
What form should these Explanations take?						
Both	6.244	3.575	3.051	1	0.081	[-0.762, 13.251]
None	3.590	2.514	2.038	1	0.153	[-1.338, 8.518]
Plain Language Descriptions	3.116	2.682	1.350	1	0.245	[-2.141, 8.374]
Visualization	0[a]	-	-	0	-	-
Opinion in AI Systems Providing Explanations for their Decisions						
No	-3.871	1.196	10.484	1	0.001	[-6.214, -1.528]
Yes	0[a]	-	-	0	-	-

The parameter estimates in Table VI provide insights into the usability and user experience of the application, considering various predictors such as the acceptability of AI in fraud detection, industry type, demographic variables, and behavioral patterns. The acceptability of AI in fraud detection significantly affects user experience, as indicated by its estimate of 1.456 and a *p*-value of .022, which is below the .05 threshold-demonstrating a positive influence on perceived usability. Similarly, the ICT industry exhibits a significant positive effect (estimate = 20.515, p = .044), suggesting that users from this sector find the application more user-friendly.

Gender differences also emerge, with females showing a significant positive impact on usability (estimate = 2.126, *p* = .025). Additionally, the threshold values for different levels of user-friendliness (e.g., [AI user-friendliness = 3]) are not statistically significant, indicating variability in subjective perceptions of usability.

Furthermore, Table 6 reveals notable patterns in users' opinions and behaviors. For instance, users who recommend the application as "Likely" or "Neutral" have negative parameter estimates (-8.621 and -9.581, respectively) with highly significant *p*-values (both < .001), suggesting that individuals in these categories are less inclined to rate the application's usability positively. Conversely, users who never engage in online social commerce significantly differ from other groups (estimate = 21.309, *p* = .033), indicating unique behavioral tendencies.

Similarly, opinions on whether AI systems should provide explanations show a negative relationship for those responding "No" (estimate = -3.871, *p* = .001), reflecting skepticism or lower satisfaction. Overall, these findings offer actionable insights for improving the application's usability across different user segments.

Objective 3: To explore the potential impact of the AI application on risk assessment and management in the online retail and social commerce domain.

Research Question 3: What is the potential impact of the AI application on risk assessment and management in the online retail and social commerce domain?

TABLE VII MODEL FITTING INFORMATION FOR EVALUATING THE POTENTIAL IMPACT OF THE AI APPLICATION ON RISK ASSESSMENT AND MANAGEMENT IN THE ONLINE SOCIAL COMMERCE DOMAIN

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	381.045			
Final	109.421	271.624	126	.000

Link function: Logit

The model fitting information in Table VII indicates that the inclusion of predictors significantly improves the model fit for assessing the potential impact of AI applications on risk assessment and management in online social commerce. The chi-square value of 271.624, with 126 degrees of freedom and a significance level of $p < .001$, confirms that the final model provides a statistically better fit than the intercept-only model.

ABLE VIII GOODNESS-OF-FIT AND PSEUDO R-SQUARE MEASURES FOR EVALUATING THE POTENTIAL IMPACT OF THE AI APPLICATION ON RISK ASSESSMENT AND MANAGEMENT IN THE ONLINE SOCIAL COMMERCE DOMAIN

	Chi-Square	df	Sig.	Pseudo R-Square	
Pearson	906.866	462	.000	Cox and Snell	0.743
Deviance	107.799	462	1.000	Nagelkerke	0.871
				McFadden	0.709

Link function: Logit

Table VIII presents the goodness-of-fit statistics for the model assessing the potential impact of AI applications on risk assessment and management in online social commerce. The Pearson chi-square value of 906.866, with 462 degrees of freedom and a significance level of $p < .001$, suggests that the model fits the data well. The deviance statistic of 107.799, with p = 1.000, indicates that the final model fits the data comparably to the saturated model. The pseudo-R-square values demonstrate a strong model fit, with Cox and Snell = 0.743, Nagelkerke = 0.871, and McFadden = 0.709, indicating that the model explains a substantial proportion of the variance in the outcome.

TABLE IX PARAMETER ESTIMATES FOR EVALUATING THE POTENTIAL IMPACT OF THE AI APPLICATION ON RISK ASSESSMENT AND MANAGEMENT IN ONLINE SOCIAL COMMERCE.

Parameter	Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval
Threshold						
[Equally effective]	48.929	6816.009	0.000	1	0.994	[-13310.202, 13408.061]
[Less effective]	49.557	6816.009	0.000	1	0.994	[-13309.575, 13408.688]
[More effective]	59.660	6816.008	0.000	1	0.993	[-13299.470, 13418.790]
Location						
[Industry = Private Sector]	-2.830	9.403	0.091	1	0.763	[-21.259, 15.600]
[Industry = Fashion]	-5.332	11.053	0.233	1	0.630	[-26.996, 16.333]
[Industry = Civil Service]	-1.100	9.578	0.013	1	0.909	[-19.873, 17.673]
[Industry = Dropshipping]	2.995	10.001	0.090	1	0.765	[-16.607, 22.598]
[Industry = Education]	-8.972	9.855	0.829	1	0.363	[-28.288, 10.344]
[Industry = Agriculture]	27.314	3054.884	0.000	1	0.993	[-5960.149, 6014.776]
[Industry = Banking/Finance]	-6.030	13.426	0.202	1	0.653	[-32.344, 20.284]
[Industry = Health sector]]	-26.882	9025.583	0.000	1	0.998	[-17716.700, 17662.936]
[Industry = Construction]	-2.577	9.964	0.067	1	0.796	[-22.106, 16.951]
[Industry = ICT]	17.520	3054.912	0.000	1	0.995	[-5969.998, 6005.038]
[Industry = IT]	-13.852	10.910	1.612	1	0.204	[-35.235, 7.531]
[Industry = Tech]	-0.474	10.666	0.002	1	0.965	[-21.380, 20.432]
[Industry = Marketing]	-8.695	9238.052	0.000	1	0.999	[-18114.945, 18097.554]
[Industry = Textile]	0.367	9.553	0.001	1	0.969	[-18.356, 19.089]
[Industry = Trading]	-3.178	16.676	0.036	1	0.849	[-35.864, 29.507]
[Industry = None]	-2.348	9.857	0.057	1	0.812	[-21.667, 16.971]
[Industry = Others]	0[a]	-	-	0	-	-
Gender						
[Gender = Female]	2.874	0.975	8.685	1	0.003	[0.963, 4.785]
[Gender = Male]	0a	-	-	0	-	-
Marital Status						
[Marital Status = Married]	1.987	3.554	0.313	1	0.576	[-4.979, 8.954]
[Marital Status = Divorced]	-0.169	1.281	0.018	1	0.895	[-2.679, 2.340]
[Marital Status = Single]	0[a]	-	-	0	-	-
Highest Educational Qualification						
[HEQ = B.Sc./HND]	0.124	3.016	0.002	1	0.967	[-5.787, 6.034]
[HEQ = ND/NCE]	-1.838	3.125	0.346	1	0.557	[-7.963, 4.288]
[HEQ = Postgraduate Degree]	4.411	3.577	1.521	1	0.217	[-2.599, 11.421]
[HEQ = Secondary School Certificate]	0[a]	-	-	0	-	-

Employment Status						
[ES = Employed]	-2.738	1.360	4.051	1	0.044	[-5.404, -0.072]
[ES = Self-Employed]	-1.615	1.451	1.238	1	0.266	[-4.459, 1.230]
[ES = Unemployed]	0^a	-	-	0	-	-
Age						
[Age = 21-30 years]	2.889	2.988	0.935	1	0.334	[-2.967, 8.746]
[Age = 31-40 years]	1.762	3.150	0.313	1	0.576	[-4.412, 7.935]
[Age = 41 years and above]	2.633	3.694	0.508	1	0.476	[-4.607, 9.872]
[Age = Under 21 years]	0^a	-	-	0	-	-
Years in Business						
[YB = 1-2 Years]	21.682	3054.879	0.000	1	0.994	[-5965.772, 6009.135]
[YB = 3-5 Years]	21.610	3054.879	0.000	1	0.994	[-5965.843, 6009.063]
[YB = 6-9 Years]	21.194	3054.879	0.000	1	0.994	[-5966.259, 6008.648]
[YB = Just Started]	24.060	3054.880	0.000	1	0.994	[-5963.394, 6011.515]
[YB = More than 10 Years]	0^a	-	-	0	-	-
Confidence in AI for Risk Management						
[High]	-1.078	0.962	1.254	1	0.263	[-2.964, 0.808]
[Low]	0^a	-	-	0	-	-
[Moderate]	0^a	-	-	0	-	-
Awareness of AI in Risk Management						
[No]	1.000	1.364	0.537	1	0.464	[-1.673, 3.672]
[Yes]	0^a	-	-	0	-	-
Examples/Instances the Respondents are Aware of.						
[Google Review]	-6.214	3.513	3.129	1	0.077	[-13.100, 0.671]
[Google Review and Gemini AI]	-2.894	0.000	-	1	-	[-2.894, -2.894]
[Google Review and Social Media]	-8.664	10.292	0.709	1	0.400	[-28.835, 11.508]
[Google Review and Trust Pilot]	-9.156	8215.684	0.000	1	0.999	[-16111.600, 16093.289]
[Google Research]	-4.415	10.093	0.191	1	0.662	[-24.197, 15.368]
[None]	-4.619	1.990	5.388	1	0.020	[-8.520, -0.719]
[Social Media Reviews]	-2.401	0.000	-	1	-	[-2.401, -2.401]
[Trust Pilot]	-2.227	10842.411	0.000	1	1.000	[-21252.962, 21248.508]
[Others]	0^a	-	-	0	-	-
Opinion on Other Tools/Methods previously used for risk Assessment and Management						
[No]	-0.669	1.315	0.259	1	0.611	[-3.247, 1.909]
[Yes]	0^a	-	-	0	-	-
AI Impact on Risk Management						
[Businesses should be made to realise how important this could be for their income]	-29.714	11196.209	0.000	1	0.998	[-21973.879, 21914.452]
[Great impact]	-83.101	0.000	-	1	-	[-83.101, -83.101]
[How effective it's going to be when implemented and it functionality]]	-33.340	0.000	-	1	-	[-33.340, -33.340]
[Impact of AI in this regard is indispensable]	-4.160	0.000	-	1	-	[-4.160, -4.160]
[None]	-30.017	3597.398	0.000	1	0.993	[-7080.787, 7020.753]

[The pass mark is Speed]	-34.927	0.000	-	1	-	[-34.927, -34.927]
[Vendorze platform owners should be indemnified against legal risk emanating from those who use their platform]	-28.750	3597.412	0.000	1	0.994	[-7079.548, 7022.048]
[Others]	0[a]	-	-	0	-	-
Suggestions for Usability Improvement						
[Ability to search within the application]	51.759	0.000	-	1	-	[51.759, 51.759]
[It should be more self-explanatory]]	22.759	3054.882	0.000	1	0.994	[-5964.700, 6010.218]
[Make it available to everyone]	43.157	0.000	-	1	-	[43.157, 43.157]
[None]	21.085	3054.868	0.000	1	0.994	[-5966.346, 6008.516]
[Shorten the questions]	-0.097	0.000	-	1	-	[-0.097, -0.097]
[The logout button shouldn't be hidden]	23.913	3054.909	0.000	1	0.994	[-5963.597, 6011.424]
[Others]	0[a]	-	-	0	-	-
Optimism about AI Integration						
[Neutral]	0.171	1.528	0.013	1	0.911	[-2.824, 3.167]
[Optimistic]	0.860	0.812	1.122	1	0.289	[-0.731, 2.451]
[Pessimistic]	-16.145	6413.493	0.000	1	0.998	[-12586.360, 12554.070]
[Very optimistic]	0[a]	-	-	0	-	-
Recommendation Likelihood						
[Likely]	-3.734	1.981	3.551	1	0.059	[-7.617, 0.150]
[Neutral]	-5.514	2.094	6.931	1	0.008	[-9.618, -1.409]
[Somewhat Likely]	-3.948	3.043	1.683	1	0.195	[-9.912, 2.017]
[Very Likely]	0[a]	-	-	0	-	-
Vendor Safety Awareness						
[Not familiar]	-6.730	2.345	8.234	1	0.004	[-11.327, -2.133]
[Somewhat familiar]	-1.388	0.858	2.614	1	0.106	[-3.070, 0.295]
[Very familiar]	0[a]	-	-	0	-	-

The parameter estimates in Table IX provide insights into the effectiveness and impact of AI applications on risk assessment and management in online social commerce. Regarding the threshold levels of perceived effectiveness, all estimates for "equally effective," "less effective," and "more effective" were statistically non-significant ($p > .05$), indicating that respondents did not report clear differentiation among the AI effectiveness categories.

For specific industries, the private sector and fashion industry reported slightly negative but non-significant parameter estimates, suggesting minimal perceived impact. Similarly, other sectors-such as civil service, dropshipping, and education-showed weak associations, with wide confidence intervals encompassing both positive and negative effects.

Gender differences revealed a significant positive association for females (estimate = 2.874, p = .003), suggesting that female respondents perceive AI as potentially more impactful than their male counterparts. In terms of employment status, a significant negative estimate for "Employed" (estimate = -2.738, p = .044) implies lower confidence in AI's risk management capabilities among employed individuals compared to unemployed respondents.

Age groups and years in business did not show a significant influence, and both confidence in AI and awareness variables also reflected non-significant estimates. However, specific awareness sources-such as "None" (estimate = -4.619, p = .020)-were significant, indicating that unfamiliarity with AI may reduce its perceived potential.

Suggestions for usability improvements, such as "Shorten the questions" (estimate = -0.097, p not reported), were not statistically significant. Meanwhile, attitudes toward AI integration showed some variation. For example, pessimism was evident, with the "Pessimistic" category showing a highly negative estimate (-16.145) but a non-significant p-value (p = .998). Lastly, vendor safety awareness revealed a significant negative association for the "Not familiar" group (estimate = -6.730, p = .004), underscoring the importance of user familiarity in shaping perceptions of AI's efficacy.

V. CONCLUSION

The AI application was perceived as "more accurate" (56.5%) or "highly accurate" (23%) in profiling risks, suggesting a high level of effectiveness. Additionally, 65% of respondents found AI to be "more effective" than traditional methods in fraud detection. Regarding usability, 60.3% of participants rated the application as "very good," and 49.7% indicated they were likely to recommend it to an acquaintance. Younger users aged 21-40 and female respondents demonstrated higher levels of satisfaction and trust in the AI system. Overall, 54% of respondents were generally optimistic, while 30.5% were very optimistic about AI integration into everyday scenarios. In terms of confidence in AI for risk management applications, 61.5% rated it as moderate and 38% as very high. However, 85% of respondents reported unfamiliarity with specific AI tools. Recommendations for improving usability included introducing chatbot services, enhancing navigation, and enabling offline functionality. Safety awareness among vendors and knowledge of AI tools had a highly significant impact on perceptions of both effectiveness and usability. Confidence in AI was lower among employed individuals compared to those who were self-employed or unemployed. The model demonstrated strong predictive power (Nagelkerke R^2 = .871), indicating that the application is well-suited for assessing and managing risk.

Declaration of Conflicting Interests

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation

The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

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