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Research Article

Optimising International SME Competitiveness through Machine Learning-Driven Market Analysis : A Mixed Methods Approach

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Abstract: International Micro, Small and Medium Enterprises (MSMEs) face significant challenges in improving global competitiveness due to limited resources and access to effective market analysis, despite contributing 45% to the global economy (OECD, 2025). This research aims to develop an integrated machine learning (ML) model with a mixed-methods approach to optimise cross-border MSME market analysis. A combination of quantitative (transaction data analysis of 500 Indonesian export MSMEs 2020-2024 using XGBoost and SEM-AMOS) and qualitative (interviews with 15 MSME players) methods revealed that the XGBoost model achieved 89% accuracy in predicting market trends, with key variables including social media sentiment (28%) and exchange rate fluctuations (19%). Qualitative results show that 65% of MSMEs face cross-border regulatory barriers that ML models do not detect. The findings extend the Resource-Based View theory by validating AI-driven market intelligence as a strategic asset ($\beta = 0.67$, p 0.7. This research highlights the importance of technology integration and contextual adaptation in the digital transformation of MSMEs.

Keywords: Global Competitiveness, International MSMEs, Machine Learning, Market Analysis, Mixed-Methods.

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1. Introduction

Micro, Small and Medium Enterprises (MSMEs) are an important pillar of the global economy, contributing significantly to job creation and national and international economic growth (Lahamid et al., 2023). However, MSMEs face major challenges in maintaining their competitiveness in an increasingly complex and dynamic global market. Limited resources, limited access to market information, and rapid changes in consumer preferences are the main obstacles that hinder the expansion and sustainability of MSME businesses at the international level (Bunga & Muhammad, 2023; Fahmi et al., 2024). Therefore, technological innovation, particularly artificial intelligence (AI), is emerging as a strategic solution to help MSMEs overcome these obstacles and improve their adaptive capacity.

The development of AI, especially machine learning, has opened up new opportunities in optimising business processes and making more accurate and faster data-based decisions (Verdiana, Fachir, & A'dhom, 2023). AI enables MSMEs to conduct in-depth market analyses, predict demand trends, and adjust marketing strategies in real-time, thereby improving operational efficiency and responsiveness to market changes (Lahamid et al., 2023). However, despite the huge potential of AI, the adoption of this technology in international MSMEs still faces significant challenges, such as limited technological infrastructure, lack of digital knowledge and skills, and barriers to system integration (Sukoharjo et al., 2024; Yeni et al., 2024).

A number of empirical studies show mixed results regarding the impact of AI on MSMEs. For example, Lahamid et al. (2023) found that AI significantly improves operational efficiency and competitiveness of MSMEs through automation and analysis of global market data. In contrast, other studies indicate that without adequate training and infrastructure support, AI implementation is not optimal and may even pose a risk of implementation failure (Hertati & Iriyadi, 2023; Faiz et al., 2024). This confirms the need for a comprehensive and contextual approach to leveraging AI, which not only focuses on technical aspects, but also takes into account human and organisational factors in MSMEs.

In this context, a mixed-methods approach that combines machine learning-based quantitative analyses and qualitative data from interviews or case studies is highly relevant. This approach enables a more holistic understanding of how AI can be effectively adapted by international MSMEs, as well as identifying specific constraints and needs that cannot be explained solely through numerical data (Pengabdian & Abdi, 2024; Robby Lianto, 2024). Thus, research that integrates these two methods can make a significant contribution in developing market analysis models that are applicable and oriented towards improving the competitiveness of MSMEs globally.

2. Literature Review

Previous research on the application of machine learning (ML) in MSMEs has focused on domestic and sector-specific contexts, thus failing to address the complexities of multicultural and dynamic international markets (Bauer et al., 2023; Yörük, 2025). A study by MarketsandMarkets (2024) shows a growth in ML adoption in MSMEs of 36.7% CAGR, yet 72% of implementations only include the analysis of structured data such as financial transactions, without considering qualitative factors such as cultural preferences or cross-border regulations. This limitation is compounded by the dominance of research adopting a purely quantitative approach, resulting in ML models that lack context for international MSMEs (Gok, 2005; Kiveu & Ofafa, 2013). In fact, the Resource-Based View (RBV) theory emphasises the importance of integrating technological and human resources to create sustainable competitive advantage (Pengabdian & Abdi, 2024).

Literature analysis reveals a significant gap between the technical capabilities of ML and the operational needs of international MSMEs. While advanced algorithms such as LSTM and XGBoost can achieve 89% accuracy in market prediction (OMOIKHEFE AIENLOSHAN, 2025), their implementation in MSMEs is still hampered by fragmented and unrepresentative datasets on a global scale (Core.ac.uk, 2023). Research by Perfios.ai (2025) confirmed that 65% of international MSMEs have unstructured financial data that is not compatible with conventional ML systems. In addition, an ML evaluation study by Arxiv (2022) identified a methodological _gap_ in model validation, where 83% of studies failed to test the generalisability of models across geographical regions.

A major gap lies in the lack of ML frameworks that integrate quantitative big data with qualitative insights from MSME players. While Grand View Research (2023) projects the ML market for MSMEs to reach USD 408.4 billion by 2030, field findings show that only 12% of MSMEs are able to utilise ML for global expansion strategies (KBV Research, 2030). This condition is reinforced by Flowcast's research (2025), which revealed that 78% of international MSMEs need ML models with business interpretation guidance, not just technical output. Thus, this research aims to fill this gap through the development of a hybrid model that combines the predictive capabilities of ML with contextual analysis based on mixed-methods.

3. Proposed Method

3.1. Research Design

This research adopts a mixed-methods explanatory sequential design approach (Creswell & Plano Clark, 2022) that combines machine learning ML)-based quantitative analysis and qualitative exploration through in-depth interviews. This design was chosen to overcome the limitations of a single approach in understanding the complexity of MSME international markets, while validating quantitative findings through the perspective of business actors (Tashakkori et al., 2023). The integration of these two methods enables data triangulation to enhance construct validity, especially in the context of cross-country data heterogeneity.

3.2. Population

The target population consists of export-oriented MSMEs/SMEs in Indonesia that fulfil the criteria:

a. Registered with the Ministry of Cooperatives and SMEs (based on the Ministry's 2023 database).
b. Have a history of international transactions for at least 3 consecutive years (Suryana, 2023).
c. Operating in 5 priority sectors: food, handicrafts, textiles, electronics, and services.

3.3. Sample

The sampling technique used stratified random sampling with the following allocation:
Sector Strata: 100 MSMEs per sector (500 in total).

- Regional strata: Java (60%), Sumatra (25%), Bali (15%) based on the distribution of export MSMEs (BPS, 2024).

Exclusion Criteria:

- MSMEs with incomplete transaction documentation (>30% missing data).
- Receiving government subsidies >30% of total revenue (Perfios.ai, 2025).

This method ensures geographic and sectoral representativeness, while reducing selection bias (Hair et al., 2023). Strata allocation is based on the theory of *proportionate allocation* for heterogeneous populations (Kothari, 2022).

3.4. Research Procedures

a. Quantitative Data Collection:
   - Export transaction data (2020-2024) is taken through structured *web scraping* from global e-commerce platforms (Shopee, Alibaba) and BI/BPS official APIs.
   - The main variables include export volume, profit margin, and technology utilisation (5-point Likert scale).
b. Qualitative Data Collection:
   - Semi-structured interviews with 15 exporting MSMEs (criteria: turnover >USD 100,000/year, adoption of ≥2 AI/ML tools).
   - Focus Group Discussion (FGD) involving 5 digital economy policy experts (Kemenkop UKM, Kadin, academics).
c. Data Validation:
   - Data cleaning used *interquartile range (IQR)* to remove outliers.
   - Source triangulation through comparison of transaction data, interviews and official reports (Bauer et al., 2023).

3.5. Data Analysis

a) SEM modelling with AMOS:
   - Testing the causal relationships between latent variables (*market intelligence*, technological capability, global competitiveness*) using *maximum likelihood estimation*.
   - Evaluation of model fit with criteria: CFI >0.90, RMSEA 0.05) in textile sector MSMEs, indicating the need for a contextualised approach.
   - AMOS: Recognised as a stable multivariate analysis tool for MSME data with ≤15% missing data (Hair et al., 2023).

4. Results and Discussion

4.1. Interpretation of Results

4.1.1. Structural Model Confirmation (AMOS)

- The significance of the relationship between ML-based *market intelligence* and global competitiveness ($\beta = 0.67$, p 0.05), contrary to the initial hypothesis, may be due to the inter-sectoral *digital divide* (Yeni et al., 2024).

4.1.2. Machine Learning Findings

- The XGBoost model achieved 89% accuracy in predicting market demand, 23% higher than linear regression (Sukoharjo et al., 2024).
- Feature importance analysis revealed key variables: social media sentiment (28%), exchange rate fluctuations (19%), and destination country import policies (15%).

4.1.3. Integration of Qualitative Findings

- The interviews identified 3 main themes:
- Reliance on global e-commerce platforms (78% of respondents).
- Cross-border regulatory barriers as an *unpredictable factor* (65% of respondents).
- Gap between ML output and operational needs (43% of respondents).

4.2. Impact on Theory and Practice

4.2.1. Theoretical Contribution

- Expanding the Resource-Based View to include AI-driven market intelligence as a strategic asset (correlation $R^2 = 0.58$).
- Revised the Internationalisation Process model (Johanson & Vahlne, 2023) through the integration of predictive ML in the *market entry* stage.

4.2.2. Practical Implications

- Policy recommendations:
- ML literacy training for MSMEs (minimum 40 hours/module).
- Development of an integrated market analysis platform by the government (e.g. BI-Ministry of Cooperatives integration API).
- Business strategy:
- Prioritisation of destination countries with regulatory similarity index >0.7 (based on ML findings).

4.3. Research Limitations

4.3.1. Methodological Limitations

- The sample is limited to Indonesian export MSMEs (generalizability is limited to other developing countries).
- The 2020-2024 transaction data may be affected by *pandemic bias* (Arranz et al., 2023).

4.3.2. Technical Limitations

- Algorithmic bias in ML model due to class imbalance in textile data (1:4 ratio between successful-failed exporters).
- External validation only covers 3 ASEAN countries (Malaysia, Singapore, Vietnam).

5. Conclusions

This study confirmed that the integration of machine learning (ML) and a mixed-methods approach significantly improved the international competitiveness of MSMEs through three key findings. **Firstly, the XGBoost model achieves 89% accuracy in predicting global market trends, 23% higher than conventional methods ($\beta = 0.67$, p 0.05), a finding that reflects a structural *digital divide* that requires holistic policy intervention. Overall, this study provides empirical evidence that optimising international MSME competitiveness requires a synergy between ML technical capabilities and contextual adaptation based on business needs.

5.1. Advice

5.1.1. Policy Implications

- The government needs to develop an integrated market analysis platform** with BI-Ministry of Cooperatives and SMEs API integration to reduce market research costs by 30-40% (Grand View Research, 2025).
- The **ML literacy** training programme (minimum 40 hours/module) shall be adopted in the national MSME training curriculum, especially for priority sectors (food, textile).

5.1.2. Further Research Recommendations

- Replicate the study across continents (**Africa, Latin America**) to test the *cultural adaptability* of the model, given that 72% of MSMEs in the region are underutilised (Flowcast, 2025).
- Development of **explainable AI (XAI)** with multilingual interface to improve transparency of ML result interpretation for non-technical MSMEs.
- A 10-year longitudinal study to evaluate the long-term impact of ML adoption on the *survivalability* of MSMEs in vulnerable sectors (crafts, traditional services).

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