Research Trends and Evolution of Machine Learning–Accounting Systems for SME Anomaly Detection

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Abstract
Micro, Small, and Medium Enterprises (MSMEs) face persistent financial governance risks due to informal accounting practices, limited digital capabilities, and weak anomaly detection mechanisms in conventional Accounting Information Systems (AIS). This study aimed to map the development, intellectual structure, thematic evolution, and research opportunities at the intersection of Machine Learning (ML), AIS, financial anomaly detection, and MSMEs. A longitudinal descriptive quantitative design was employed using bibliometric analysis and science mapping of 202 Scopus-indexed articles and review papers published between 2018 and 2026. Data were processed using RStudio-bibliometrix, Biblioshiny, and VOSviewer through performance analysis, keyword co-occurrence analysis, thematic mapping, clustering, and thematic evolution analysis. The findings revealed rapid growth in this research field, with an annual growth rate of 60.48% and a publication peak in 2025. Four major thematic clusters were identified: financial forensics, ensemble algorithms, deep learning, and the SME operational context. Random Forest and XGBoost emerged as particularly promising approaches for resource-constrained MSMEs due to their efficiency, predictive accuracy, and interpretability. However, the field remains fragmented, computationally oriented, and limited in terms of validation using authentic MSME datasets. The study concluded that future intelligent AIS development should integrate predictive performance, accounting controls, class-imbalance handling, explainable artificial intelligence (XAI), user acceptance, and broader international collaboration to support transparent, practical, and preventive financial governance in small businesses worldwide.

INTRODUCTION

Micro, Small, and Medium Enterprises (MSMEs) represent a vital pillar of economic growth, particularly in developing nations, by absorbing significant labor, strengthening local economic activities, expanding entrepreneurial opportunities, and supporting community economic resilience. However, despite this strategic contribution, MSMEs continue to face fundamental challenges in financial governance. Their operational characteristics, which are often flexible, simple, and informal, frequently result in poorly documented and inconsistent transaction processes. This structural informality increases the risk of accounting errors (Vasarhelyi et al., 2015), fund misallocation, financial leakages, and fraudulent activities. Unlike large corporations that typically have dedicated internal audit divisions, multi-layered control procedures, and mature accounting frameworks, many MSMEs still rely on manual record-keeping systems or basic financial software. This reliance is further compounded by limited skilled human resources, low levels of accounting and digital literacy (Schmitz & Leoni, 2019), and restricted budgets for technological investment, making financial transaction monitoring less effective. Consequently, abnormal or irregular transactions are often not detected at an early stage, and business owners may only identify financial deviations after significant and irreversible losses have occurred.

To contextualize this issue, conventional Accounting Information Systems (AIS) are primarily designed to record, classify, summarize, and report financial transactions to support financial reporting and operational decision-making. However, conventional AIS has significant limitations in detecting financial anomalies because it is predominantly retrospective, recording events after they occur rather than providing real-time early warnings before risks develop into actual losses. This limitation is particularly critical for MSMEs due to their limited capacity to absorb financial disruptions (Schmitz & Leoni, 2019). The integration of artificial intelligence (Sutton et al., 2016), particularly machine learning (ML), has emerged as a relevant approach for addressing these limitations by enabling systems to learn historical transaction patterns, identify unusual financial behaviors, detect anomalies, and generate early warnings for potentially suspicious transactions. This transformation allows AIS to evolve from a passive recording system into an intelligent, adaptive, and preventive financial monitoring system, consistent with broader research demonstrating that artificial intelligence and data analytics are driving significant transformations in accounting, auditing, internal control systems, and data-driven organizational (Kokina & Davenport, 2017; Moll & Yigitbasioglu, 2019; Wamba et al., 2017).

Despite this potential, a significant transdisciplinary gap remains because computer science, accounting, auditing, and MSME management have historically developed along separate research trajectories. From a computer science perspective, advanced anomaly and fraud detection models, such as Isolation Forest, Random Forest, XGBoost, Support Vector Machines, and Neural Networks, have demonstrated strong predictive performance in data-driven experiments. However, these technical approaches often emphasize algorithmic optimization while paying limited attention to essential accounting principles, including double-entry bookkeeping, audit trails, regulatory compliance, and interpretability requirements for non-technical users (Abdallah et al., 2016; Ngai et al., 2011; West & Bhattacharya, 2016a). Conversely, accounting and auditing research primarily focuses on improving recording procedures, internal controls, financial reporting, and compliance. Although contemporary auditing literature emphasizes the importance of data analytics, continuous auditing, and automation, practical implementation among MSMEs remains insufficiently explored due to technological, financial, and human resource limitations (Alles, 2015; Appelbaum et al., 2017). This fragmentation has slowed the development of intelligent AIS solutions tailored to MSMEs, creating a gap between technically advanced models that may be difficult for small business owners to adopt and user-friendly accounting applications that lack predictive anomaly detection capabilities.

Therefore, the main research problem addressed in this article concerns the absence of a cohesive transdisciplinary framework that integrates machine learning algorithms with the practical, affordable, and user-centered operational realities of MSME accounting. Addressing this issue requires evaluating the convergence of ML and AIS not only through algorithmic performance but also through considerations of user acceptance, model transparency, implementation costs, business process integration, and the specific characteristics of MSME transactions. Although scientific publications on machine learning algorithms and financial data analytics have increased substantially, the integration of these technologies with accounting information systems specifically designed for MSME operational and socio-technical conditions remains fragmented and underdeveloped across disciplines.

Accordingly, this study aimed to conduct a comprehensive (Phua et al., 2010) bibliometric and science mapping analysis using the Scopus database to systematically examine global literature published from 2018 to 2026 concerning the intersection of anomaly detection methods, ML technologies, AIS frameworks, and MSME business contexts (Mongeon & Paul-Hus, 2016). Specifically, this study addressed eight bibliometric research questions: (1) how global scientific production trends have developed regarding the convergence of ML and AIS for financial anomaly detection in MSMEs; (2) what document characteristics, publication types, source journals, and research profiles dominate this field; (3) how international collaboration and geographical distribution are structured across countries; (4) what conceptual structures emerge from author keyword co-occurrence networks; (5) what strategic positions, development levels, and maturity stages characterize the identified thematic clusters; (6) how research themes have evolved over time; (7) what productivity patterns and contributions characterize influential authors in this domain; and (8) what scientific gaps remain for future research opportunities. By addressing these questions, this study contributes theoretically by connecting the Technology Acceptance Model (TAM), forensic accounting, and fraud analytics, emphasizing that algorithmic capabilities must align with perceived usefulness and ease of use among non-technical users (Davis, 1989). Practically, this study provides a foundation for system developers, auditors, and policymakers to design affordable, transparent, and integrated anomaly detection features within AIS, enabling MSMEs to progress from basic digital record-keeping toward predictive financial governance systems that support fraud prevention and long-term economic resilience.

METHOD

This study employed a longitudinal descriptive quantitative design using bibliometric analysis and science mapping to systematically examine the intellectual structure and research evolution at the intersection of Machine Learning (ML), Accounting Information Systems (AIS), financial anomaly detection, and Micro, Small, and Medium Enterprises (MSMEs). This methodology was selected because it enabled the objective analysis of large-scale bibliographic datasets by transforming unstructured metadata into traceable intellectual and structural networks, thereby addressing limitations commonly found in conventional subjective literature reviews (Aria & Cuccurullo, 2017; Donthu et al., 2021). The research data consisted of peer-reviewed scientific publications indexed in global academic databases, while the research focus was directed toward conceptual relationships, algorithmic integration, and the application scope of ML-based anomaly detection within MSME financial management contexts. The study used the Scopus database as the primary data source, with the analyzed literature covering a nine-year period from 2018 to 2026 to capture recent technological developments and research trends. The overall data collection process and ML–AIS bibliometric analysis workflow are presented in Figure 1.

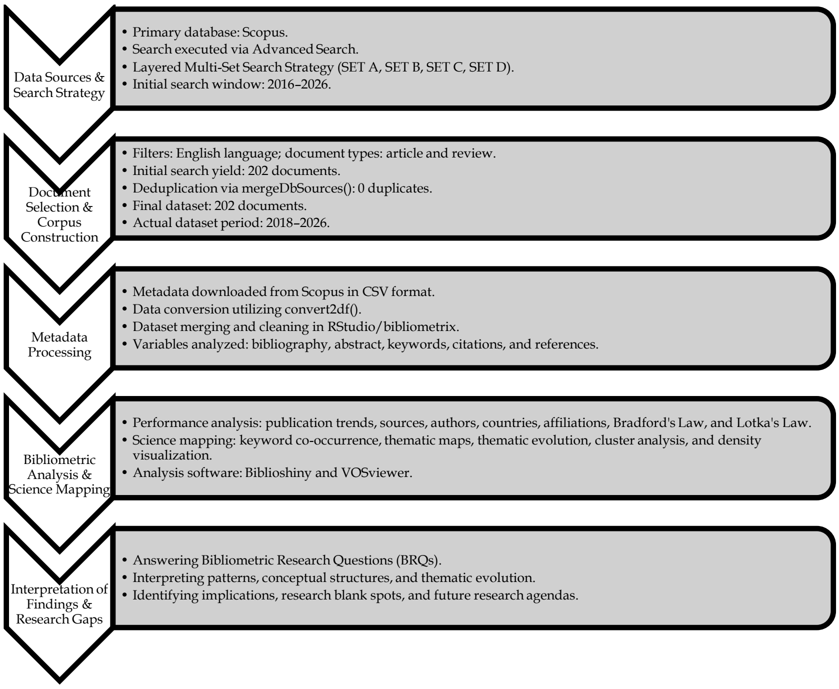

Figure 1. Data Corpus Construction and ML-AIS Bibliometric Analysis Flowchart. Source: Data processed according to Aria and Cuccurullo (2017), (Zupic & Čater, 2015), and Donthu, Kumar, Mukherjee, Pandey, and Lim (2021).

The sampling method followed a purposive, non-probability, criteria-based approach implemented through a layered multi-set search strategy within the Scopus advanced search interface. This approach was applied to minimize excessive filtering while ensuring the retrieval of relevant documents. Scopus was selected as the primary data source due to its rigorous indexing standards, comprehensive metadata coverage, and extensive use in previous bibliometric studies (Mongeon & Paul-Hus, 2016).

The data collection process involved retrieving bibliographic information by organizing the research domain into four conceptual sets representing the main thematic pillars: (1) anomaly and fraud detection, (2) machine learning and artificial intelligence techniques, (3) accounting systems and transactional frameworks, and (4) the operational context of MSMEs. The initial search period covered 2016–2026; however, because documents meeting all combined criteria were identified from 2018 onward, the final analyzed corpus consisted of publications from 2018 to 2026. The retrieved metadata were limited to English-language articles and review papers to maintain consistency in keyword co-occurrence analysis. Conference proceedings, book chapters, and editorials were excluded to ensure the quality and consistency of the peer-reviewed dataset. The query structure, conceptual framework, and resulting document distribution are presented in Table 1.

Table 1. Layered Multi-Set Search Strategy and Sampling Results

Query Set	Core Conceptual Combination	Search String Formulation	Initial Yield
SET A	Anomaly Detection × Machine Learning × Accounting Systems	TITLE-ABS-KEY (("anomaly detection" OR "fraud detection" OR "suspicious transaction*" OR "financial anomal*") AND ("machine learning" OR "artificial intelligence" OR "deep learning" OR "intelligent algorithm*") AND ("accounting information system*" OR "accounting system*" OR "financial transaction*" OR "digital bookkeeping")) AND PUBYEAR > 2015 AND PUBYEAR < 2027 AND (DOCTYPE (ar) OR DOCTYPE (re))	175
SET B	Machine Learning × Accounting Systems × MSME Context	TITLE-ABS-KEY (("machine learning" OR "artificial intelligence" OR "deep learning" OR "intelligent algorithm*") AND ("accounting information system*" OR "accounting system*" OR "financial transaction*" OR "digital bookkeeping") AND ("SME" OR "SMEs" OR "small business*" OR "small and medium enterprise*" OR "UMKM")) AND PUBYEAR > 2015 AND PUBYEAR < 2027 AND (DOCTYPE (ar) OR DOCTYPE (re))	12
SET C	Anomaly Detection × Accounting Systems × MSME Context	TITLE-ABS-KEY (("anomaly detection" OR "fraud detection" OR "suspicious transaction*" OR "financial anomal*") AND ("accounting information system*" OR "accounting system*" OR "financial transaction*" OR "digital bookkeeping") AND ("SME" OR "SMEs" OR "small business*" OR "small and medium enterprise*" OR "UMKM")) AND PUBYEAR > 2015 AND PUBYEAR < 2027 AND (DOCTYPE (ar) OR DOCTYPE (re))	0
SET D	Anomaly Detection × Machine Learning × MSME Context	TITLE-ABS-KEY (("anomaly detection" OR "fraud detection" OR "suspicious transaction*" OR "financial anomal*") AND ("machine learning" OR "artificial intelligence" OR "deep learning" OR "intelligent algorithm*") AND ("SME" OR "SMEs" OR "small business*" OR "small and medium enterprise*" OR "UMKM")) AND PUBYEAR >	15

Query Set	Core Conceptual Combination	Search String Formulation	Initial Yield
		2015 AND PUBYEAR < 2027 AND (DOCTYPE (ar) OR DOCTYPE (re))	
Total Accumulated Rough Documents			**202**
R Control System Deduplication (mergeDbSources)			**0**
Final Clean Dataset Total			**202**

Following data retrieval, the metadata were exported in CSV format (.csv), containing relevant fields such as titles, abstracts, author keywords, index keywords, citations, and institutional affiliations. Data processing and deduplication were conducted in RStudio using the open-source bibliometrix package. The raw files were converted into structured data frames using the convert2df() function. Subsequently, datasets from the active search blocks were merged using the mergeDbSources() function with duplicate removal procedures applied. This process ensured that overlapping records were eliminated, resulting in a final cleaned dataset of 202 documents. The zero-yield result from SET C provided an initial indication that research on fraud or financial anomaly detection within MSME accounting structures remained limited when examined independently from machine learning or artificial intelligence integration.

Data analysis employed two bibliometric tools: Biblioshiny, the web-based interface of the R-bibliometrix package, was used to analyze publication growth, (Bradford, 1934a), while VOSviewer was used to visualize keyword co-occurrence networks, conceptual clusters, and density maps (van Eck & Waltman, 2010). The analysis was conducted in two sequential phases. First, performance analysis applied descriptive bibliometric indicators to evaluate publication trends, citation impact, and the productivity of authors, journals, affiliations, and countries from 2018 to 2026. Second, science mapping was conducted to examine the conceptual and intellectual structure of the ML–AIS research domain through keyword co-occurrence analysis, thematic mapping, clustering, and thematic evolution analysis. These approaches collectively identified major research patterns, thematic developments, and research gaps that provide directions for future empirical investigations.

RESULTS AND DISCUSSION

The final dataset evaluated in this study consists of 202 peer-reviewed Scopus documents published during the active longitudinal window from 2018 to 2026. Although the initial literature search strategy captured a wide baseline matrix from 2016 to 2026, scientific documents meeting the strict intersection of machine learning algorithms, accounting frameworks, and small business dimensions only began to surface in 2018. To establish a transparent overview of the structural landscape, the foundational macro-bibliometric parameters of this finalized data corpus are compiled and synthesized in Table 2.

Table 2. Macro-Bibliometric Metadata Parameters of the ML-AIS Dataset (2018–2026)

No	Description	Results
A	**Main Information About Data**	
1	Timespan	2018:2026
2	Sources (Journals, Books, etc)	137
3	Documents	202
4	Annual Growth Rate %	60.48
5	Document Average Age	1.84
6	Average citations per doc	14.12
7	References	18493
B	**Document Contents**	
1	Keywords Plus (ID)	823
2	Author's Keywords (DE)	677
C	**Authors**	
1	Authors	707
2	Authors of single-authored docs	21
D	**Authors Collaboration**	
1	Single-authored docs	22
2	Co-Authors per Doc	3.66
3	International co-authorships %	26.24
E	**Document Types**	
1	article	192
2	review	10

Source: Data processing result, 2026

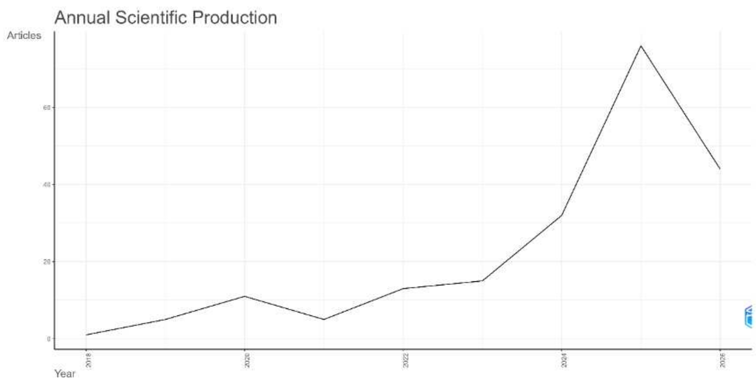

Figure 2. Annual Trajectory Graph of ML-AIS Global Scientific Production (2018–2026).
Source: Data processed by R Studio, 2026

The chronological trajectory of global scientific production bridging machine learning, accounting information systems, financial anomaly detection, and MSME frameworks reveals an accelerating research domain. As illustrated in Figure 2, the earliest publications materialized in 2018, followed by a gradual and steady accumulation of literature in the initial years, before experiencing an exponential surge after 2024. The peak of scientific output within this observed timeframe occurred in 2025, yielding 76 documents. It is important to interpret the data for the year 2026 with caution, as it represents the current ongoing year and the Scopus indexing pipeline for recent publications remains incomplete; thus, the visible drop at the tail end of the graph does not represent a decline in academic interest. Overall, the field exhibits a remarkable annual growth rate of 60.48%, signifying an intense escalation of scientific inquiry.

Evaluating the dispersal of publication channels using Bradford's Law reveals that the core journals driving this domain are heavily rooted in computational science, data analytics, artificial intelligence, and digital information systems (Bradford, 1934b). The core zone, mapped out in Figure 3, is dominated by prominent outlets such as IEEE Access, Scientific Reports, Computational Economics, Journal of Big Data, and Frontiers in Artificial Intelligence.

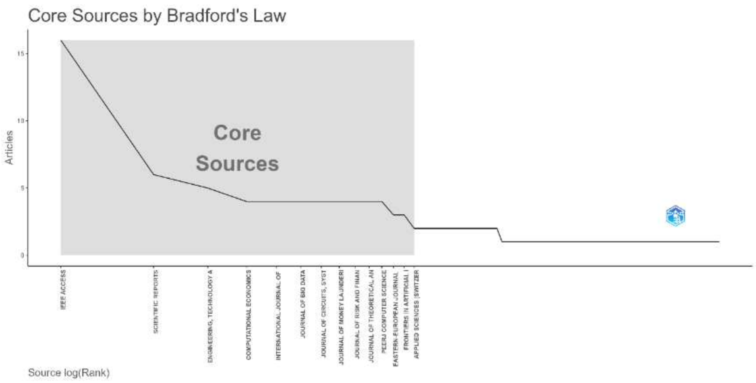

Figure 3. Core Journal Curve Based on Bradford's Law.
Source: Data processed by R Studio, 2026

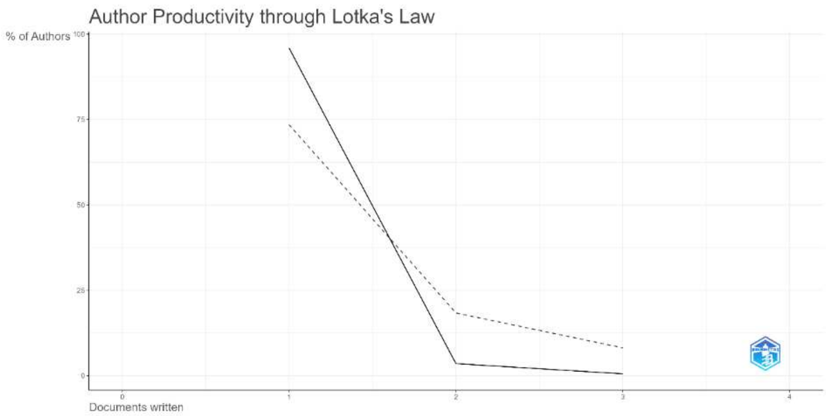

Figure 4. Author Productivity Distribution Based on Lotka's Law.
Source: Data processed by R Studio, 2026

Complementing this source analysis, the distribution of author productivity analyzed via Lotka's Law reveals a highly fragmented and decentralized authorship structure (Lotka, 1926). As displayed in the mathematical distribution in Figure 4, approximately 95% of the participating scholars have contributed only a single document to this corpus. This pattern indicates that the ML-AIS research domain is still expanding outward, with authorship widely dispersed rather than consolidated around a small cadre of dominant authorities. This dynamic is further detailed in Figure 5, which tracks top author productivity over time; pioneering scholars such as Liu Z and Li J laid the algorithmic groundwork during the earlier phases, whereas contemporary actors like Zhang X, Yang Y, Bhowmik B, and Cai M have emerged as highly prominent contributors leading up to the 2025–2026 period.

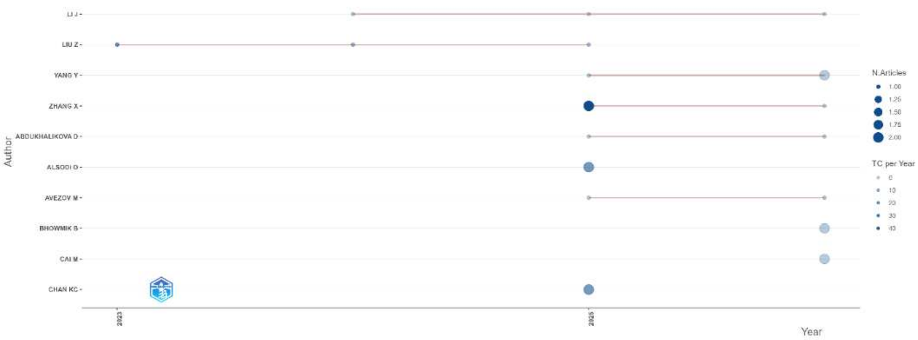

Figure 5. Top Authors' Productivity Over Time.
Source: Data processed by R Studio, 2026

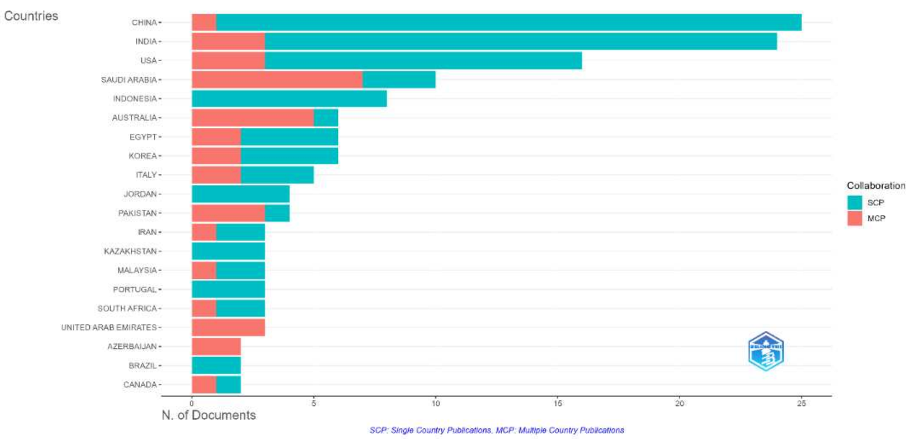

Figure 6. Distribution of Corresponding Authors' Countries.
Source: Data processed by R Studio, 2026

On a macro-geographic level, assessing the distribution of corresponding authors' countries exposes clear imbalances in global research leadership. As visualized in Figure 6, China, India, and the United States stand out as the primary powerhouses driving scientific production in ML-driven financial anomaly detection. Indonesia also establishes a visible presence within this global ecosystem with eight publications; however, a critical nuance is that all Indonesian documents are classified strictly as Single Country Publications, highlighting a clear lack of cross-border scholarly integration. This geographic concentration is mirrored at the institutional level in Figure 7, where entities such as Islamic Azad University and Prince Sattam Bin Abdulaziz University lead the global output. From an Indonesian standpoint, Satya Wacana Christian University and Diponegoro University surface as the most relevant local contributors within the corpus. When mapping the global spatial distribution of literature across the world atlas in Figure 8, the highest densities are clustered across Asia, North America, parts of Europe, the Middle East, Africa, and Australia, positioning Indonesia as a key regional contributor within Southeast Asia.

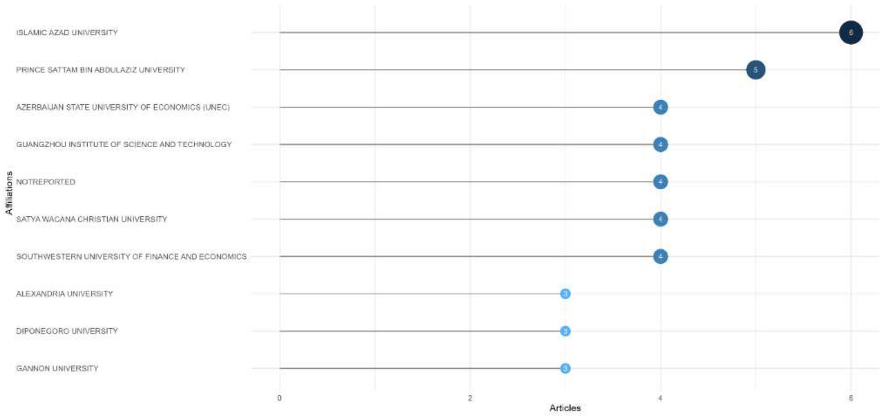

Figure 7. Most Relevant Academic Affiliations.
Source: Data processed by R Studio, 2026

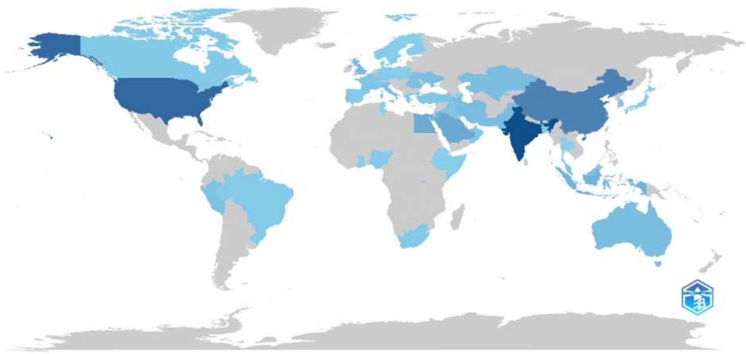

Figure 8. World Map of Country-Specific Scientific Production
Source: Data processed by R Studio, 2026

The underlying conceptual architecture of the literature can be dissected through keyword frequency treemaps, which expose how the domain is mentally structured by the scientific community. As illustrated in the proportional treemap in Figure 9, the author keywords converge into three major thematic blocks. The first block encompasses the financial forensics domain, featuring terms like fraud detection, crime, and anomaly detection, which directly align with foundational and contemporary paradigms in statistical fraud monitoring and financial irregularity detection (Bolton & Hand, 2002; Hilal et al., 2022). The second block represents intelligent computing, highlighting techniques such as machine learning, deep learning, artificial intelligence, random forest, and XGBoost, which are standard for modeling complex tabular financial data (Breiman, 2001; Chen & Guestrin, 2016) . The third block represents the broader transactional ecosystem, dominated by terms like financial transactions, finance, credit cards, financial fraud, and blockchain (Kshetri, 2018).

Figure 9. Proportional Keyword Frequency Treemap Diagram.
Source: Data processed by R Studio, 2026

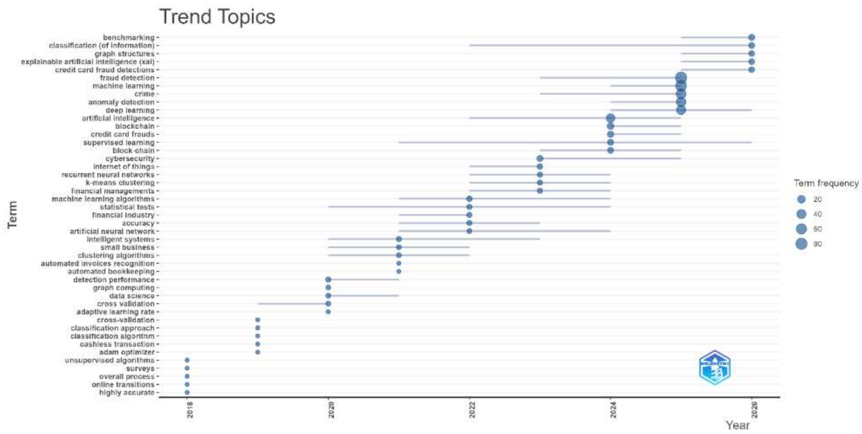

Figure 10. Dynamic Evolution of Keywords Over Time.
Source: Data processed by R Studio, 2026

The chronological evolution and shifting focus of these keywords over time reveal how the research paradigm has matured. As shown in the temporal overlay in Figure 10, the initial 2018–2019 phase focused primarily on raw algorithmic exploration and testing the basic capacity of machine learning to identify data outliers. By 2020–2021, the literature began shifting toward practical financial applications, introducing terms such as automated bookkeeping, invoice recognition, and small business. This operationalization expanded during 2022–2023 with the rise of cybersecurity, the Internet of Things, and advanced machine learning algorithms. Finally, the contemporary 2024–2026 window shows a powerful convergence toward fraud detection, anomaly detection, deep learning, graph structures, benchmarking, and explainable artificial intelligence, mirroring a global academic movement demanding both high predictive power and transparency in automated accounting systems (Murphy et al., 2024; West & Bhattacharya, 2016b; Yang et al., 2026).

To evaluate how these concepts structurally interact, a fractional counting keyword co-occurrence network was constructed. As visualized in Figure 11, the cognitive space divides into four highly interconnected clusters: (1) financial forensics, (2) ensemble algorithms, (3) deep learning, and (4) the SME operational context. The financial forensics cluster concentrates heavily on identifying transaction anomalies and operational fraud. The ensemble algorithm cluster groups classical yet robust tabular methods such as XGBoost, Random Forest, Decision Trees, and Logistic Regression. The deep learning cluster represents a shift toward structural complexity, incorporating graph neural networks and deep sequence modeling. Meanwhile, the SME context cluster demonstrates that small business operational realities have successfully entered the global discourse, though they remain on the periphery rather than acting as a central anchor of the primary network structure.

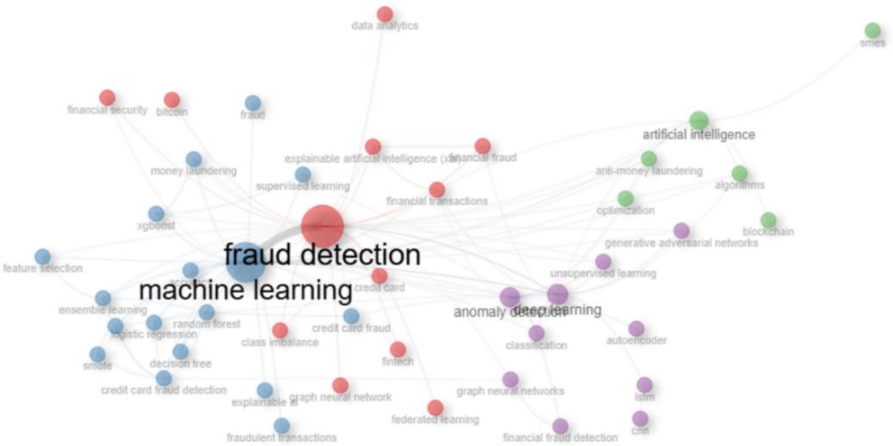

Figure 11. Author Keyword Co-occurrence Network.
Source: Data processed by R Studio, 2026

By plotting these themes onto a strategic cartography map based on Callon's density and centrality metrics, we can diagnose their structural maturity. As illustrated in the thematic map in Figure 12, financial fraud detection, graph neural networks, federated learning, and unsupervised learning position themselves firmly as motor themes, indicating high internal density and central relevance to the broader field. Conversely, concepts like the Technology Acceptance Model (TAM), SMEs, digital transformation, and credit scoring are relegated to niche themes, showing they are isolated and less developed despite their strategic importance. This thematic fragmentation is further mapped as a chronological flow in Figure 13, illustrating how foundational themes like generic machine learning, artificial intelligence, and basic fraud have sequentially split and evolved into specialized sub-domains including advanced XGBoost architectures, Autoencoders, Graph Neural Networks, and Federated Learning.

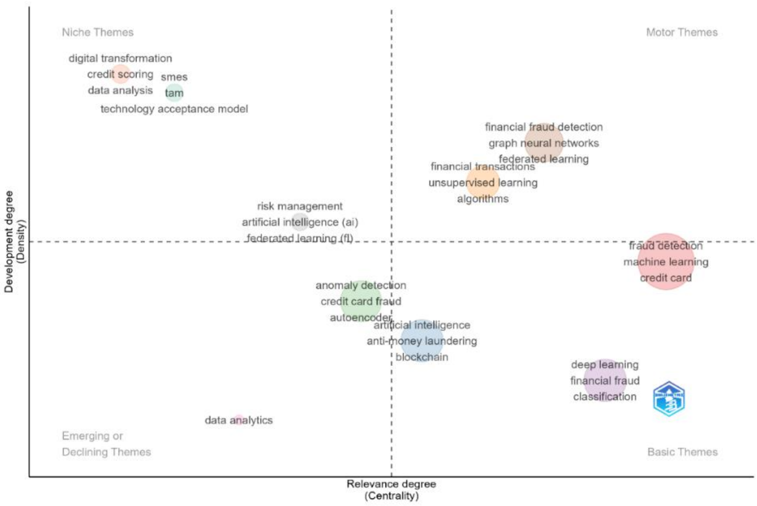

Figure 12. Thematic Map Based on Callon's Quadrants.
Source: Data processed by R Studio, 2026

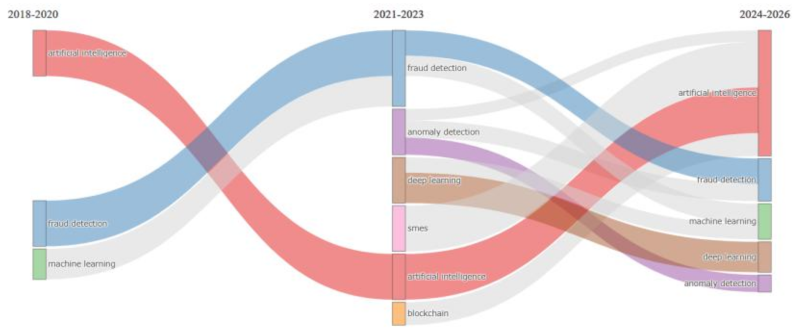

Figure 13. Thematic Evolution Flow Diagram.
Source: Data processed by R Studio, 2026

The overarching cognitive concentration of the entire domain is summarized via the density visualization map in Figure 14, where the brightest regions highlight machine learning and fraud detection as heavily saturated research areas. In contrast, specialized methodologies such as imbalanced data handling, XGBoost, Random Forest, Graph Neural Networks, Federated Learning, Blockchain, and Explainable AI remain in the dimmer, less populated zones of the map. This visual contrast marks the transition from purely reporting statistical metrics to critical academic discussion. The high concentration of generic ML and fraud concepts, juxtaposed against the dimness of specialized implementations, confirms that while the broader intersection of artificial intelligence and fraud detection is popular, its explicit engineering into tailored AIS frameworks for the resource-constrained MSME sector remains profoundly underdeveloped.

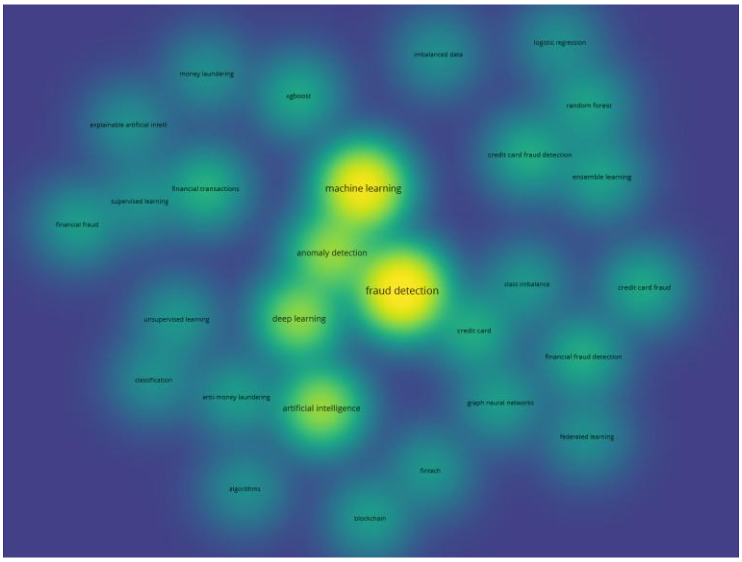

Figure 14. Thematic Density Visualization for Novelty Space Identification.
Source: Data processed by Vosviewer, 2026

Reflecting on these findings, the trajectory of the literature indicates that the convergence of machine learning and accounting information systems for MSME anomaly detection is a rapidly accelerating yet fundamentally immature field. The sudden surge in documentation after 2024 and an annual growth rate of 60.48% demonstrate that the global research community increasingly recognizes the necessity of migrating AIS from a retrospective recording tool to a predictive governance infrastructure. Instead of treating accounting systems as mere historic logs, modern paradigms treat them as active digital internal control environments capable of real-time risk mitigation. However, this rapid expansion remains volatile; the scarce number of comprehensive review papers combined with the fact that 95% of authors have published only a single document implies that the domain is highly fragmented, lacking sustained research agendas and suffering from inconsistent terminologies.

A critical structural issue exposed by this bibliometric mapping is the severe dominance of the computational perspective over accounting logic. Because the primary publication engines are technical journals like IEEE Access and Scientific Reports, financial anomaly detection is treated almost exclusively as a mathematical optimization challenge. While this technical focus accelerates algorithmic innovation and predictive accuracy, it creates a dangerous disconnect from core accounting imperatives such as double-entry verification, immutable audit trails, regulatory compliance, and system explainability for non-technical managers. For small businesses, this gap is catastrophic. An algorithm that scores high accuracy in an isolated data science lab is practically useless within an MSME operational setting characterized by poor data infrastructure, low digital literacy, and tight cost constraints. Therefore, the literature must shift from merely comparing algorithmic benchmarks to designing systems that are fundamentally usable, auditable, and embedded into daily bookkeeping workflows.

This structural misalignment is exacerbated by the deep conceptual fragmentation between machine learning methodologies and the actual operational realities of MSMEs. The peripheral position of the SME cluster in the co-occurrence network indicates that while small businesses are frequently cited as a justification for research, they are rarely used as the empirical foundation for model design. Instead, most anomaly detection models are built using massive datasets derived from credit card networks, enterprise banking, or large-scale e-commerce platforms. This creates a severe methodological mismatch, as MSME financial data is fundamentally different: it is small-scale, highly imbalanced, structurally incomplete, often corrupted by manual human error, and heavily dependent on the subjective recording habits of the owner. Consequently, models trained on clean, high-velocity institutional data cannot be dropped into an MSME environment without extensive adaptation regarding feature selection, computational weight, and user interface simplicity.

The theoretical implications of these findings point directly toward the urgent need for a transdisciplinary framework that unifies forensic accounting, data analytics, and technology acceptance theories. The isolation of TAM, digital transformation, and SMEs within the niche quadrant reveals that the human and organizational factors governing technology adoption are largely ignored by mainstream ML developers. A system cannot prevent fraud if users find it too complex to operate or too opaque to trust. Therefore, future theoretical models must posit that the efficacy of an intelligent AIS is a function of both its algorithmic accuracy and its perceived ease of use and usefulness (Venkatesh et al., 2003). Integrating explainability metrics directly into the forensic accounting framework is essential to move past the "black box" dilemma, ensuring that automated flags can be interpreted and validated by standard accounting personnel.

From a practical development standpoint, the data suggests that building intelligent AIS for MSMEs should avoid overly complex, computationally heavy deep learning frameworks in favor of robust ensemble methods. Algorithms like Random Forest and XGBoost offer a far more realistic baseline for small businesses because they require significantly less computational power, handle tabular financial data exceptionally well, and are inherently more interpretable than deep neural architectures (Breiman, 2001; Chen & Guestrin, 2016). Furthermore, system architects must elevate class imbalance from a minor preprocessing step to a primary design consideration, deploying specialized techniques like SMOTE to prevent normal transaction volumes from masking rare fraudulent activities (Chawla, Bowyer, Hall, & Kegelmeyer, 2002; He & Garcia, 2009). Crucially, to make these systems actionable for non-technical business owners, developers must integrate explainable AI (XAI) frameworks like SHAP or LIME to provide clear, variable-level justifications for every transaction flagged as an anomaly (Arrieta et al., 2020; Lundberg & Lee, 2017; Ribeiro, Singh, & Guestrin, 2016).

Ultimately, this mapping illuminates several critical research blank spots that define the future agenda of the field. First, there is an absolute scarcity of studies testing anomaly detection models on authentic, messy MSME operational datasets rather than clean public benchmarks. Second, a major empirical gap exists for hybrid frameworks that simultaneously address predictive accuracy, class imbalance, and model interpretability within low-cost software environments. Third, while cutting-edge paradigms like Graph Neural Networks, Federated Learning, and Blockchain represent the frontier of motor themes, their socio-technical feasibility within the resource-constrained MSME sector remains unmapped and demands rigorous cost-benefit validation (Dou, 2020; Li, 2020). Finally, for emerging economies like Indonesia, there is an urgent need to transition from isolated, single-country publications to collaborative international research designs. By connecting local MSME data realities with global algorithmic expertise, future transdisciplinary research can successfully transform AIS from passive ledger tools into active, intelligent shields that protect small business financial resilience.

The bibliometric results indicate that research regarding the convergence of machine learning and accounting information systems for financial anomaly detection in MSMEs is still in its nascent stages but experiencing rapid acceleration. The initiation of publications in 2018 and the exponential increase in document volume after 2024 demonstrate that this field has entered a critical growth phase. An annual growth rate of 60.48% further reflects the surging academic attention toward leveraging machine learning frameworks for financial transaction oversight. Conceptually, this expansion indicates a paradigm shift in the role of AIS, moving away from retrospective transaction-recording engines toward highly predictive analytics environments. AIS is no longer perceived merely as a mechanism for historical documentation and financial reporting, but is increasingly positioned as a digital internal control infrastructure capable of supporting the early detection of irregular transactions. However, rapid quantitative expansion does not automatically signify field maturity. The scarcity of comprehensive review papers and the fact that a vast majority of scholars have contributed only a single document imply that the broader research agenda remains fundamentally unstable, leaving the domain open to terminological fragmentation, algorithmic redundancy, and weak integration with foundational accounting theories.

The underlying drivers of this growth further reveal that the primary momentum within the ML-AIS domain originates strongly from the computer science, data analytics, and artificial intelligence communities. The distinct dominance of computational journals highlights that financial anomaly detection is still predominantly treated as a purely technical and algorithmic optimization problem rather than an accounting challenge. This technical asymmetry presents a double-edged sword; on one hand, it drives rapid advancements in predictive modeling, structural optimization, and the exploration of novel architectures. On the other hand, an overemphasized technical approach risks neglecting the unique imperatives of AIS, such as double-entry bookkeeping validation, immutable audit trails, regulatory compliance reporting, and user-facing interpretability for non-technical managers. For small business environments, this disconnect is particularly severe. Highly accurate models validated in controlled data science environments are often impractical within an MSME operational landscape plagued by fragmented data tracking, acute human resource deficits, prohibitive technology costs, and low digital literacy. Consequently, ML-AIS research must pivot from simple algorithmic benchmarking to the socio-technical design of accounting systems that are usable, explainable, auditable, and seamlessly integrated into daily transaction processing.

This technical and operational misalignment is further reinforced by the conceptual fragmentation separating machine learning techniques, accounting systems, and actual MSME operational realities. Central scientific mapping demonstrates that while the emergence of an explicit small-and-medium enterprise cluster indicates that small businesses have entered the global academic discourse, this cluster remains peripheral rather than serving as the central gravity of the primary network structure. This positions an empirical vulnerability where MSMEs are frequently invoked as a contextual justification, yet they rarely form the empirical bedrock for model design. Instead, a large portion of contemporary literature borrows datasets and assumptions from large-scale corporate environments, such as credit card networks, commercial banking systems, and macro-e-commerce platforms. However, MSME financial data possesses distinct non-linear characteristics; it is typically small-scale, structurally incomplete, highly imbalanced, susceptible to manual errors, and deeply dependent on the idiosyncratic recording behaviors of owner-managers. Therefore, anomaly detection models optimized for high-velocity institutional data cannot be assumed to function effectively for MSMEs without rigorous methodological adaptation, specifically regarding class imbalance management, relevant accounting feature extraction, business process synchronization, and the simplified visualization of results for local decision-makers.

From a theoretical perspective, the findings demonstrate that intelligent, machine-learning-driven AIS requires an integrative framework combining forensic accounting, data-driven fraud analytics, and technology acceptance. Forensic accounting establishes the foundations of auditability, evidentiary trails, and irregularity identification, while machine learning enables automated anomaly detection. However, the thematic isolation of user acceptance, digital transformation, and small businesses indicates that behavioral and organizational dimensions remain insufficiently integrated with algorithm development. Therefore, intelligent AIS should not focus solely on predictive performance but also incorporate accounting principles, explainability, organizational readiness, and user acceptance to ensure effective implementation within MSMEs.

From a practical perspective, intelligent AIS for MSMEs should prioritize computationally efficient and interpretable ensemble methods, particularly Random Forest and XGBoost, which are well suited to tabular financial data and resource-constrained environments (Breiman, 2001; Chen & Guestrin, 2016). Class imbalance should also be addressed systematically because fraudulent transactions are substantially less frequent than legitimate transactions, potentially producing misleading accuracy measures. Techniques such as SMOTE can improve minority-class detection (Chawla, Bowyer, Hall, & Kegelmeyer, 2002; He & Garcia, 2009). Furthermore, integrating explainable artificial intelligence approaches, such as SHAP and LIME, can provide transparent explanations of anomaly alerts, supporting decision-making by MSME owners and auditors (Arrieta et al., 2020; Lundberg & Lee, 2017; Ribeiro, Singh, & Guestrin, 2016).

Several research gaps emerge from this mapping. First, empirical validation using authentic MSME transaction data remains limited. Second, future studies should develop cost-efficient architectures that integrate predictive accuracy, class-imbalance management, and model explainability. Third, although Graph Neural Networks, Federated Learning, and Blockchain represent promising technological directions, their economic and socio-technical feasibility for resource-constrained MSMEs requires further empirical investigation (Dou et al., 2020; Kshetri, 2018; Li et al., 2020). Finally, stronger international collaboration, particularly involving emerging economies such as Indonesia, is needed to connect local MSME evidence with global research networks. Addressing these gaps can support the transformation of AIS from passive financial-recording systems into intelligent tools for anomaly detection and financial risk management.

CONCLUSION

This study concluded that the convergence of Machine Learning (ML) and Accounting Information Systems (AIS) for financial anomaly detection in MSMEs represented an emerging research field that had developed rapidly since 2018. The bibliometric findings addressed the research objectives by mapping the field's longitudinal development, intellectual structure, conceptual framework, and future research opportunities. Four major thematic clusters were identified: financial forensics, ensemble algorithms, deep learning, and the SME operational context. The findings indicated a shift from isolated algorithmic experimentation toward operational digital internal control systems, with Random Forest and XGBoost emerging as promising approaches for resource-constrained MSMEs due to their computational efficiency, predictive accuracy, and interpretability. The study also highlighted the importance of integrating algorithmic performance with accounting principles, auditability, accountability, model interpretability, and user acceptance. Accordingly, the combination of ensemble models with class-imbalance handling techniques and Explainable Artificial Intelligence (XAI) provides a promising direction for developing intelligent AIS.

However, this study had several limitations, including reliance on Scopus-indexed articles and review papers, exclusion of conference proceedings, the inherent limitations of bibliometric analysis, and incomplete indexing coverage for 2026. Future research should incorporate multiple academic databases, validate machine learning models using authentic MSME transaction datasets, and develop explainable intelligent AIS prototypes supported by broader international collaboration.

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