Received: 15 January 2026 | Accepted: 28 May 2026
DOI: 10.52898/ijif.2026.5

ORIGINAL ARTICLE

MAPPING FINANCIAL CRIMES IN THE INSURANCE INDUSTRY: A BIBLIOMETRIC ANALYSIS OF MONEY LAUNDERING AND FRAUD LITERATURE

Eyyüp Ensari ŞAHİN
Ceyda AKTAN
Melikşah AYDIN

Authors Notes:
Correspondence
Assoc. Prof., Niğde Ömer Halisdemir University, Faculty of Economics and Administrative Sciences, Department of Finance and Banking,
ORCID: 0000-0003-2110-7571
ensarisahin@ohu.edu.tr

Assoc. Prof., Ankara Hacı Bayram Veli University, Department of Business Administration,
ORCID: 0000-0001-7040-4711
ceyda.aktan@hbv.edu.tr

Research Assistant, Niğde Ömer Halisdemir University, Faculty of Economics and Administrative Sciences, Department of Finance and Banking,
ORCID: 0000-0001-7711-1874
maydin@ohu.edu.tr

Abstract
Money laundering (ML) remains a persistent threat to the integrity and transparency of the global financial system, increasingly exploiting sectors beyond traditional banking. Among these, the insurance industry represents a particularly vulnerable yet underexplored domain due to its complex product structures, reliance on intermediaries, and comparatively fragmented compliance infrastructure. This study provides a comprehensive bibliometric assessment of financial crime research in the insurance industry, with particular emphasis on anti-money laundering (AML) and insurance fraud studies. Rather than treating these concepts as identical phenomena, the study examines how they coexist within the broader financial crime literature and how their thematic boundaries have evolved over time. Bibliographic data were retrieved from the Web of Science Core Collection using a Boolean search strategy combining "insurance" with "anti-money laundering" or "fraud." Following a multi-stage screening process (2005–2025, English-language, peer-reviewed publications, and relevance-based manual validation), a final dataset of 121 documents was analyzed using Bibliometrix (R) and VOSviewer. Findings reveal that research output has grown unevenly over time, often responding to regulatory shifts and digital transformation rather than cumulative theoretical development. The literature is characterized by fragmentation across journals and institutions, with notable geographic concentration in high-income countries and limited international collaboration. Co-word and thematic analyses identify five major clusters: algorithmic fraud detection, behavioral ethics, regulatory compliance, sector-specific applications (e.g., motor and health insurance), and jurisdictional policy contexts. The results further highlight the increasing prominence of machine learning and explainable AI concepts, yet emphasize a persistent gap in integrating algorithmic tools with institutional and ethical governance frameworks. Overall, this study contributes a structured overview of financial crime research in the insurance industry, particularly focusing on money laundering and fraud.

Keywords
Insurane, mapping financial crimes, money aundering and fraud.

JEL Classification
G22, E44.

1. INTRODUCTION

Money laundering continues to be a threat to the integrity and transparency of the global financial system. From a conceptual perspective, ML is the process of making financial gains that are unjustified by integrating them into the formal economic system, this will lead to the concealment of their origin (He, 2010; Bagaskara & Yanti, 2025). This procedure is typically composed of three separate operational steps: placement, layering, and integration. Through this procedure, the sources of illegal funds are consistently concealed (Gilmore, 1995; Tiwari et al., 2020). Although money laundering is commonly associated with criminal activities such as drug trafficking, terrorism financing, and extortion, quasi-legal financial sectors are becoming increasingly important in facilitating these activities. (Schneider & Windischbauer, 2008; Schneider, 2010). These processes collectively diminish the legitimacy of institutions, misallocate resources, and threaten to disrupt the macro-economic balance.

The continued existence of money laundering schemes can be explained through multiple theoretical perspectives. Regulatory arbitrage theory is concerned with the exploitative rationalities of illegal actors that benefit from institutional failures and regulatory asymmetries in sectors like insurance, this is particularly true of compliance enforcement in these fields (Kane, 1981). Meanwhile, behavioral economics provides a behavioral framework for understanding the rationalization strategies of individuals operating in highly opaque environments (Kahneman & Tversky, 1979). Institutional theory further explains how regulatory structures, reliance on intermediaries, and internal governance structures facilitate or hinder money laundering (DiMaggio & Powell, 1983). These theoretical fields collectively argue that money laundering is not simply a technical or operational challenge but a deeply embedded socioeconomic and institutional phenomenon that requires a multi-scale analytical approach.

Although historically overshadowed by the banking sector in the anti-money laundering (AML) literature, the insurance industry exhibits unique and multifaceted vulnerability characteristics. From a regulatory perspective, the Financial Action Task Force (FATF) has repeatedly identified life insurance products as potentially vulnerable channels for money laundering due to their investment-like characteristics and the possibility of early surrender or transfer of benefits (FATF, 2004; FATF, 2023). Similarly, the International Association of Insurance Supervisors (IAIS), through Insurance Core Principle 22 (ICP 22), emphasizes the necessity of implementing a risk-based AML/CFT framework tailored to insurance activities. These developments demonstrate that AML concerns in insurance extend beyond traditional fraud prevention and require sector-specific compliance mechanisms that address product design, customer due diligence, and beneficial ownership transparency. High-risk insurance products—including single-premium life insurance, annuities, and unit-linked insurance contracts—allow illicit funds to be deployed and consolidated under the guise of legitimate financial planning (Dalla Pellegrina & Masciandaro, 2009). Payments upon maturity or early termination mimic regular financial activity while concealing the proceeds of crime. Compared to the banking sector, the insurance industry's compliance infrastructure remains relatively fragmented. Transaction monitoring, suspicious activity reports, and onboarding checks are considered inadequate (Bagaskara & Yanti, 2025).

From an economic perspective, the insurance industry plays a dual role: serving as both a long-term institutional investor and a conduit for capital accumulation. Beyond compliance considerations, the economic effectiveness of AML policies remains an important area of debate. Truman and Reuter (2004) argue that despite substantial investments in AML systems, empirical evidence regarding their effectiveness remains limited. Likewise, Levi (2017) highlights the challenges associated with measuring the true costs and benefits of AML frameworks. In the insurance industry, where compliance expenditures continue to increase alongside digital transformation initiatives, understanding the balance between regulatory costs and crime prevention benefits has become an increasingly relevant research concern. However, complex product configurations, multifaceted client relationships, and reliance on third-party intermediaries such as brokers and reinsurers make the industry particularly vulnerable to money laundering schemes involving shell companies, undeclared beneficiaries, and synthetic claims (Ferwerda & Reuter, 2019; Ramada, 2022; Ofoeda et al., 2022). In this context, the fraud triangle theory offers insight: opportunities arise from weak controls and complex transactions, pressures are reinterpreted as speculative profiteering, and a lack of transparency and regulatory tolerance provide fertile ground for these activities (Acharya, 2015). According to Cressey (1953), fraudulent behaviour emerges from the interaction of pressure, opportunity, and rationalization.

Despite the implementation of standardized AML protocols—customer due diligence, customer identification procedures, know-your-customer, and transaction monitoring—the insurance industry remains underrepresented in policy discussions and academic research (Kuzmenko et al., 2020). Thanasegaran and Shanmugam (2008) point out three persistent misconceptions: that insurance products are illiquid, that initial risk assessments are sufficient, and that surrender penalties reduce the incentive to launder money. However, the increasing complexity of money laundering theories has rendered these assumptions obsolete. Recent regulatory changes indicate an increasing concern with these issues. International organizations like the Financial Action Task Force (FATF) recommendations and the subsequent EU anti- laundering directive have now identified types of money laundering that are specific to the insurance industry. Furthermore, Walker and Unger (2013) emphasize that money laundering should be understood as a global economic phenomenon driven by both the supply of illicit funds and the demand for laundering opportunities. Their structural modelling approach suggests that financial sectors differ substantially in terms of laundering attractiveness and regulatory exposure. Despite these insights, the role of insurance markets within the broader laundering ecosystem remains comparatively underexplored, creating an important gap in the literature. Additionally, the increasing popularity of artificial intelligence (AI) and machine learning (ML) technologies is catalyzing a new approach to AML. These instruments have the potential to reduce false positives, improve the detection of anomalous behavior, and automate compliance processes (Hernandez Aros et al., 2024; Weber et al., 2018; Ghosh, 2020). However, the integration of these tools into AML in the insurance industry is still in its infancy, the majority of applications focus on retail banking or capital markets (Bhattacharyya et al., 2011; Eling & Lehmann, 2018).

As compliance tasks shift from manual oversight to automated systems, new concerns arise regarding model interpretability, ethical accountability, and regulatory transparency. Industries like insurance, characterized by their complex structures and information asymmetries, require a high degree of interpretability and industry-specific calibration. However, the literature on AI in AML remains largely siloed, lacking a comprehensive perspective that captures the intersection between computational tools, institutional behavior, and regulatory expectations. This study addresses this gap through a targeted bibliometric analysis of the scholarly landscape in the area of money laundering in the insurance industry. This study maps influential contributions, thematic clusters, geographic trends, and disciplinary intersections to guide academic research and regulatory practice. Specifically, this study makes the following contributions: (i) identifies the core intellectual structure of insurance-related anti-money laundering research; (ii) assesses the interdisciplinary intersections between artificial intelligence, finance, and regulation; (iii) tracks the evolution of money laundering typologies; (iv) reveals research gaps in explainable artificial intelligence in the insurance anti-money laundering field; and (v) provides methodological considerations on the utility of bibliometric tools in analyzing specific financial crime topics. Crucially, the bibliometric analysis is conceptually grounded in three overlapping theoretical paradigms: behavioral economics, regulatory governance, and institutional theory. Fraudulent behavior is understood both as an adaptive strategy and as a systemic product influenced by information asymmetry, compliance culture, and evolving regulatory thresholds. Therefore, this study provides not only a descriptive account but also a theoretical framework for exploring the cognitive evolution of AML discourse – from a passive compliance model to a proactive algorithmic framework.

Based on the identified gap in the literature, this study addresses the following research questions:

RQ1: What are the publication and citation trends in financial crime research related to the insurance industry?

RQ2: Which authors, institutions, countries, and journals have contributed most significantly to the development of this field?

RQ3: What thematic clusters and intellectual structures characterize insurance-related financial crime research?

RQ4: How have research themes evolved over time, particularly regarding AML, insurance fraud, and emerging technological solutions?

RQ5: What future research directions can be identified from the existing bibliometric structure?

2. METHODOLOGY

This research systematically analyzes the scientific literature pertaining to financial crimes in the insurance industry using quantitative bibliographic methods. Bibliometric analysis calculates the scientific merits of a subject by observing the increasing popularity of publications, influential authors, institutional contributions, and the long term evolution of a topic (Ellegaard & Wallin, 2015). Because of the fragmentation and the lack of research in this field, bibliometric methods are structured around the exploration of the intellectual landscape of the field.

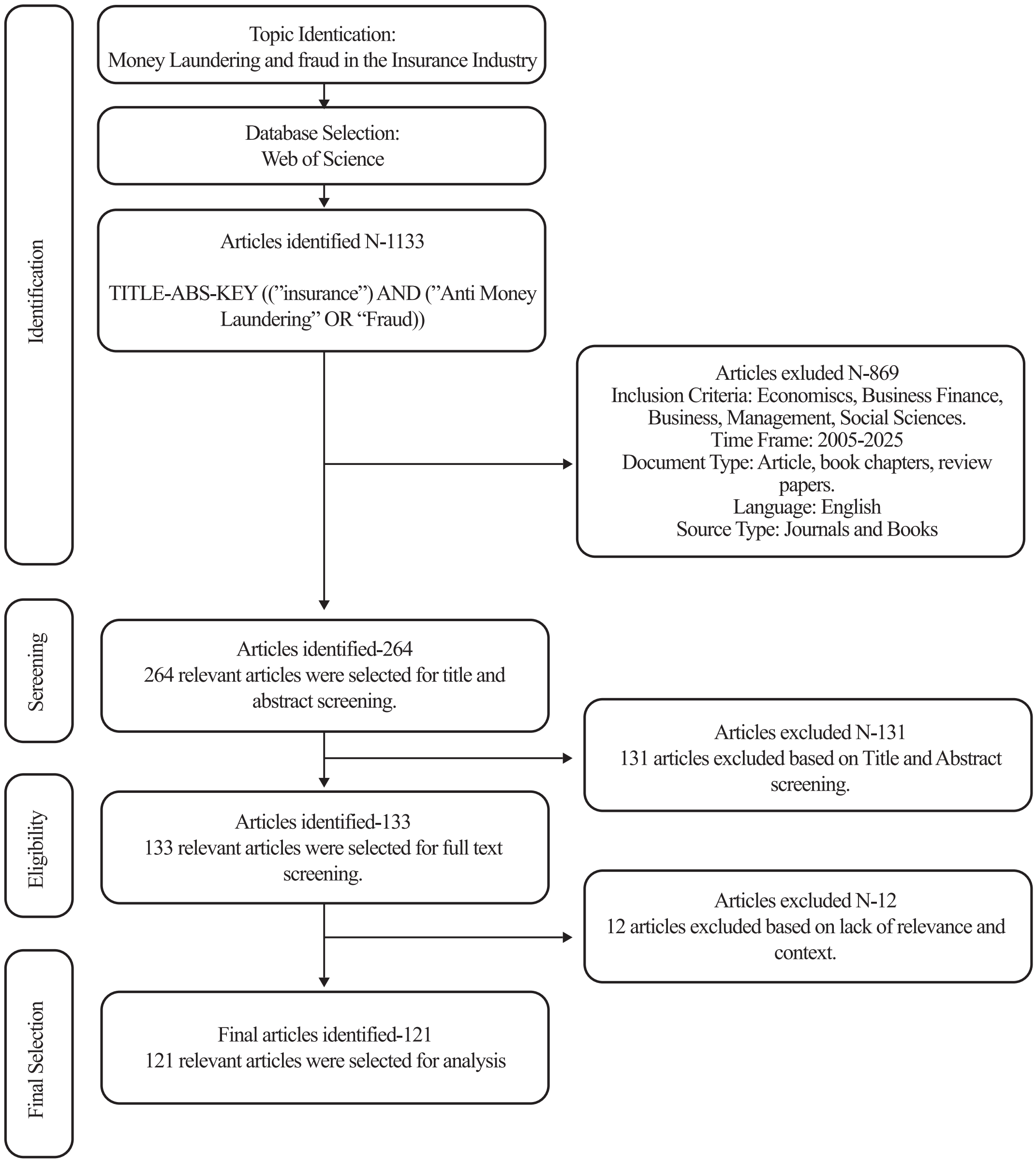
Beyond its technical capacity, bibliometric analysis is derived from the scientometric approach, which suggest that the scientific literature is a complex system of knowledge production. This perspective concords with Kuhn's theory of scientific evolution, which involves the investigation of how publications and coauthor patterns are associated with communities of knowledge and shifts in discipline. This methodology is based on a constructivist perspective of fields of research as being the result of a developing cognitive structure rather than being a static concept. In this regard, bibliometrics not only calculates the amount of research output, but also captures the evolving concepts and institutions that are involved in the discussion of money laundering in the insurance industry.

In VOSviewer, keyword co-occurrence analysis was conducted using full counting. The minimum keyword occurrence threshold was set at 3. Association strength normalization was applied, and clustering was performed using the VOS clustering algorithm with the default resolution parameter. Network visualization and cluster detection were subsequently cross-validated using Bibliometrix.

2.1. Data Source and Collection

The research's bibliographic data was sourced from the Web of Science (WoS) Core Collection, which is a recognized database of high-quality, peer-reviewed literature in fields like law, criminology, finance, and economics. WoS was chosen because of its comprehensive coverage, standardized data on citations, and compatibility with bibliometric software that facilitates performance and mapping of science. Data were extracted on June 2025. Since 2025 represents a partial publication year, it was retained for descriptive purposes but excluded from growth-rate interpretations.

Diagram 1
Prisma 2020 Flow Diagram



To recognize pertinent publications, a Boolean search strategy was developed using the following query: (“insurance”) AND (“anti-money laundering” OR “fraud”). The initial hunt for literature on the intersection of money laundering and other topics related to insurance, including prevention of fraud, compliance with regulations, and the practice of regulatory agencies. The initial hunt yielded 1133 documents, with no limitations on language, type of document, or year of publication. The open-ended query was formulated according to a bibliometric approach that prioritized recall over precision in the initial phase, this was done in order to ensure that the query was topical and included all of the subject. Through a broad keyword search, the study maximized the capture of intellectual contributions that would otherwise be dissociated from disciplines.

2.2. Inclusion and Exclusion Criteria

To further reduce the dataset, various procedures were employed. First, publications were limited to the time period 2005-2025, which included two decades of scholarly output, historical and current events. Second, only English-language publications were considered to ensure the consistency of the

Keyword analysis. Third, the dataset was limited to articles that were peer-reviewed, book chapters, and review articles; scientific content that was conference-based, editorials, and non-scientific were all excluded. Additionally, the results were limited by selecting only articles that were indexed in relevant disciplines regarding business, including corporate finance, entrepreneurship, and social sciences that are related to business management, including management and organization theory. After following these rules, the dataset was reduced to 264 written works.

While bibliometric analysis provides a comprehensive overview of the field, it does not evaluate the qualitative nature or scientific merits of individual publications. Additionally, keyword-based searches may overlook relevant literature that employs alternative terminology or is misclassified (Donthu et al., 2021). As a result, titles and abstracts were individually reviewed to ensure that they were relevant to the topic. Studies that did not directly discuss financial crimes, money laundering, or insurance fraud within the insurance industry were excluded. This clarification ultimately led to a sample of 121 publications that constituted the core dataset for the bibliometric study. This hybrid method which combines algorithmic processing and human review balances both comprehensiveness and topical accuracy. It also addresses the issues associated with fully automated search strategies regarding complex, interdisciplinary research topics like money laundering in insurance, where the terminology used and the way it is indexed is both inconsistent and biased.

2.3. Data Processing and Analysis

The curated dataset was exported from Web of Science in BibTeX format and imported into two complementary bibliometric tools: Bibliometrix (an R package) and VOSviewer. Web of Science was preferred because of its standardized indexing structure and compatibility with bibliometric software. Prior to analysis, the data was cleaned to remove duplicate records and standardize key terms.

Bibliometrix was used to conduct performance analysis, including annual scientific output, citation trends, and identification of the most productive authors, institutions, and journals. Furthermore, science mapping techniques were applied to explore the conceptual, intellectual, and social structures of the field, including co-citation analysis and thematic development. VOSviewer was used to create network visualizations, specifically mapping co-authorship networks and keyword co-occurrence patterns. This provided insights into the collaborative dynamics between researchers and major thematic clusters that shape the literature on money laundering in the insurance industry. This dual tool triangulation enhanced the robustness of the analysis by cross-validating results between different bibliometric logics: statistical logic (Bibliometrix) and visual-relational logic (VOSviewer). This combination facilitated the identification of both macro-trends and micro-structural features, such as emerging subfields or epistemic bottlenecks. In VOSviewer, keyword co-occurrence analysis was conducted using full counting. The minimum keyword occurrence threshold was set at 3. Association strength normalization was applied, and clustering was performed using the VOS clustering algorithm with the default resolution parameter. Network visualization and cluster detection were subsequently cross-validated using Bibliometrix.

3. FINDINGS

Table 1
Data Statistics

Description	Results
Timespan	2005:2025
Sources (Journals, Books, etc)	80
Documents	121
Annual Growth Rate %	1,7
Document Average Age	8,61
Average citations per doc	10,64
References	3996
Document Contents	
Keywords Plus (ID)	274
Author's Keywords (DE)	397
AUTHORS	
Authors	274
Authors of single-authored docs	26
Authors Collaboration	
Single-authored docs	29
Co-Authors per Doc	2,64
International co-authorships %	28,1
Document Types	
article	108
article; book chapter	4
article; early access	4
article; proceedings paper	2
review	3

To ensure transparency and validity, Table 1 summarizes the data used in this bibliometric study. The data are from the WoS database and comprise 121 documents, including 108 journal articles, 4 book chapters, 4 early access articles, 2 proceedings papers, and 3 review articles. These documents are sourced from 274 authors and 80 different sources, and contain 3,996 references, with an average of 10.64 citations per document. Of the 121 studies, 26 were single-authored, meaning 95 were co-authored, with 28.1% of these co-authors comprising international co-authors. The overall characteristics of the dataset reflect the emerging and fragmented nature of academic research on money laundering in the insurance industry. The relatively low annual growth rate (1.7%) and low proportion of international co-authors (28.1%) suggest that the field lacks the cognitive cohesion often seen in established research areas. These data also indicate that research is often confined to isolated national or institutional contexts, limiting cross-national theory building or comparative analysis.

Furthermore, the average publication age of the papers is 8.61 years, and the average number of citations per paper is 10.64, indicating a moderate level of citation intensity in the field. This may be due to the selectivity of the literature search—or perhaps due to the heterogeneity of the research niche or methodologies. From a scientometric perspective, this citation dynamic generally indicates that the field is still in a consolidation phase; while foundational work exists, a self-reinforcing citation structure or core theory has yet to emerge.

The proportion of collaborative papers and the diversity of publication types (e.g., early access articles, book chapters) also suggest a degree of experimental publishing strategy, potentially reflecting the multidisciplinary nature of the subject, which lies at the intersection of criminology, finance, regulatory science, and information science. Therefore, this table not only summarizes descriptive data but also suggests the need for more comprehensive and theory-driven research collaborations to unify this fragmented knowledge landscape.

Figure 1
Annual Scientific Production

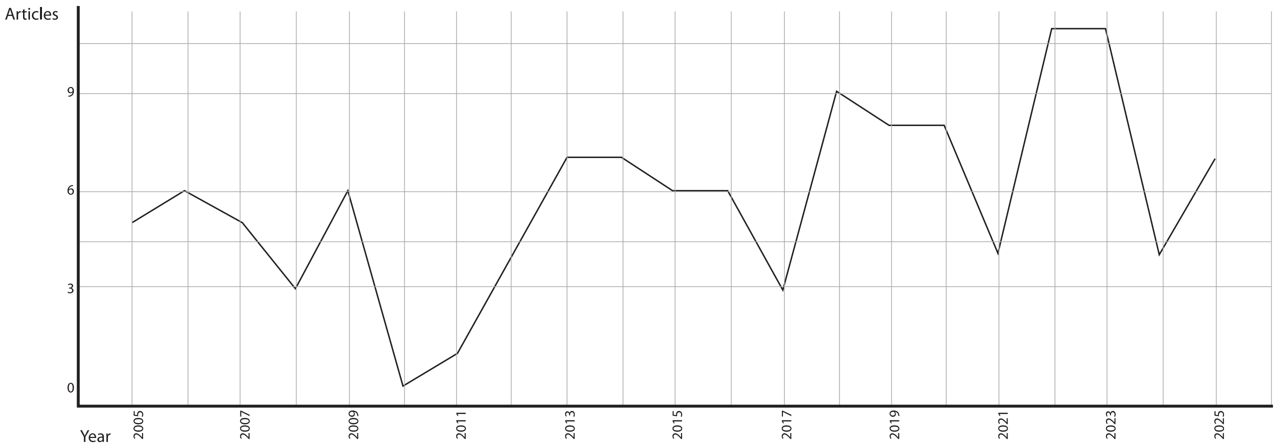
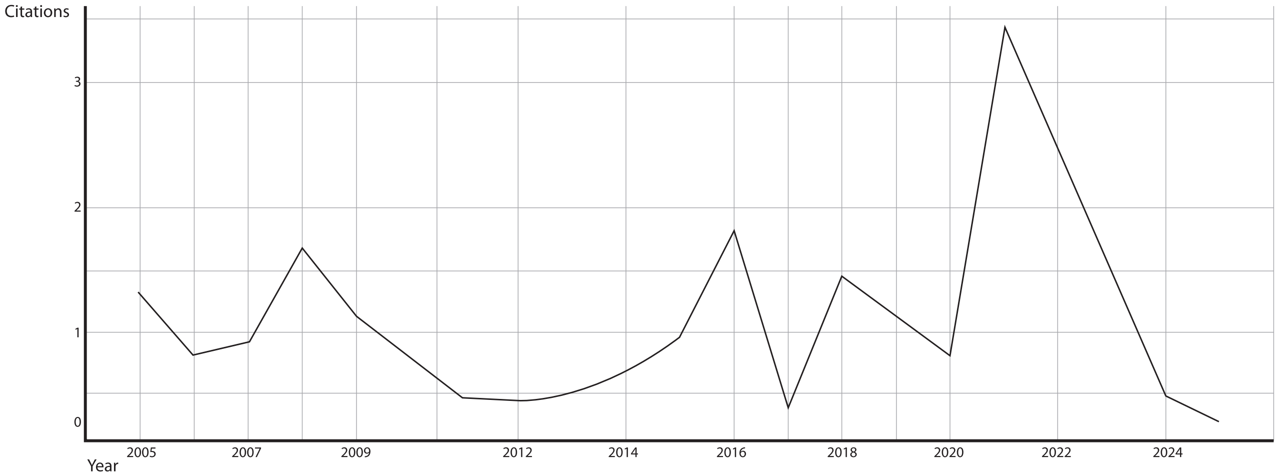


Figure 1 shows annual scientific output from 2005 to 2025. The observed fluctuations likely reflect structural, institutional, and contextual factors influencing research output in the field. According to the graph there is a sharp decline in 2010. This period may be related to the aftermath of the 2008 global financial crisis, when scholars' attention may have focused on risk management, banking regulation, or financial recovery, leading to a decrease in scholarly attention to money laundering and the insurance industry. However, publication activity increased during 2013–2014. This period overlaps with important regulatory developments in international AML governance; however, no causal relationship can be established based solely on publication trends. In 2022, following the COVID-19 pandemic, research output increased significantly. This period was characterized by the increasing digitalization of financial services, which heightened the need for more substantive AML governance.

Beyond these contextual drivers, the pronounced fluctuations in scholarly output also reflect the field's cognitive maturity. These dramatic fluctuations suggest that the scholarly discussion on insurance-related money laundering is highly reactive, often influenced by external crises and regulatory changes rather than internal theoretical integration. This temporal fluctuation may also indicate a fragmented academic base, with research outputs sporadic rather than cumulative, dependent on funding windows, compliance changes, or technological disruptions. For example, the observed increase between 2013 and 2014 may be related not only to the momentum of FATF reforms but also to the emergence of new analytical frameworks, such as behavioral compliance models and early AI-driven fraud detection tools. Similarly, the post-pandemic surge in 2022 signals not only digitalization but also a reorientation of the insurance industry's internal discussion around institutional trust and data governance. Thus, Figure 1 illustrates the changing pattern of scholarly attention over time.

Figure 2
Average Citations per Year



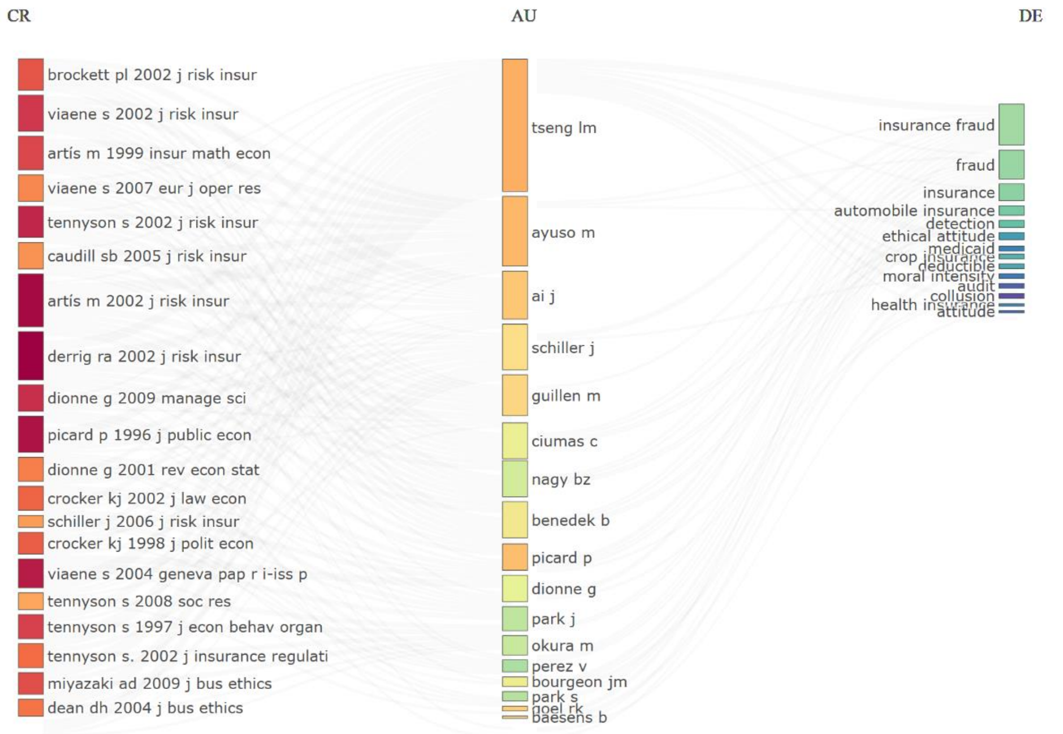
As shown in Figure 2, the average annual citations for the publications analyzed in this study exhibit diverse trends. Beyond straightforward fluctuations, this citation curve provides important insights into the field's internal maturity and external resonance. The low citation rates between 2005 and 2015 suggest a lack of core works that underpin the cumulative research. In scientometric terms, this implies a lack of a "core literature" or "paradigm text" that typically drives citation dynamics and thematic convergence.

The increase in citations after 2016 may reflect the emergence of significant interdisciplinary contributions and the rise of discussions on AI-assisted fraud detection (Kaur and Saini, 2024), which has drawn attention from related fields such as data science, behavioral finance, and regulatory studies. Therefore, this growth can be interpreted not only as a sign of growing interest but also as a signal of expanding understanding insurance money laundering is beginning to intersect with broader technology and compliance narratives.

However, particularly striking is the sharp decline in citations after 2022. This is partly due to natural citation lags, but it may also indicate saturation of earlier topics or a lack of groundbreaking theoretical contributions in recent years. In other words, the field may be entering a plateau, with increasing publication output (see Figure 1) but declining impact diffusion—highlighting a widening gap between output and impact. This underscores the urgent need for more theoretical development, methodological innovation, and cross-disciplinary dialogue to revitalize scholarly engagement.

Taken together, Figures 1 and 2 reflect the discrepancy between the number of scholarly publications and their cumulative scholarly impact. While Figure 1 shows a steady increase in publications (especially after 2016) the average citation count in Figure 2 reaches a significant peak around 2020 and then declines sharply. This temporal gap suggests that while the topic's visibility has increased, the cognitive appeal of recent research findings remains limited. This pattern may indicate a need for further theoretical and methodological diversification.

Figure 3
Tree-Field Plot



The dendrogram also known as a Sankey diagram shown in Figure 3 visually illustrates the relationships between three data elements: cited references (CR), authors (AU), and descriptors (DE). The arrangement of these elements indicates content-based and citation-based connections within the literature. Gray connecting lines represent the co-occurrence of these three elements. Stronger and more frequent connections indicate a more structurally cohesive literature landscape. Therefore, thicker gray lines indicate more frequent relationships between elements.

The first element in the left column of the chart lists the most frequently cited references, many of which come from specialized journals in fields such as risk management, insurance, mathematical economics, and operations research. The presence of these sources indicates that the field utilizes both quantitative and analytical methods to study topics such as fraud, regulatory compliance, and risk assessment in the insurance context. These references can be considered references from a wide range of authors, highlighting their key role in shaping the current research agenda. The middle column of Figure 3 shows the most frequently appearing and active authors in the dataset. Studies cited across a broad range of author nodes can be considered groundbreaking contributions that have significantly influenced methodological decisions and theoretical frameworks. The central importance of authors such as Tseng L.-M. and Ayuso M. not only demonstrates their fruitful output but also their anchoring role in bridging disciplinary logics. Their work serves as a medium through which insights from mathematics, actuarial science, and behavioral science converge in insurance fraud-related discourse.

The last column of the dendrogram displays key descriptors extracted from the dataset. “Insurance fraud,” “fraud,” and “insurance” are the most important keywords in the dataset, highlighting its core focus. However, key descriptors such as “automobile insurance,” “detection,” and “moral stance” reveal some concentrated clustering within the research. Thus, Figure 3 goes beyond structural visualization to reflect the cognitive foundations of the field, demonstrating how knowledge flows from basic research (CR) to active contributors (AU) and, by extension, to thematic areas (DE). The coexistence of descriptors such as “ethical attitude”, “moral intensity”, and “collusion” alongside traditional keywords such as “insurance fraud” and “detection” reveals a hybrid thematic structure. This suggests a conceptual bridge between institutional analysis and mental models of misconduct. In other words, the field is evolving toward a multi-layered understanding of money laundering risk—one that encompasses regulatory compliance, technical detection, and individual-level ethical reasoning.

Methodologically, the figure also demonstrates disciplinary diffusion: cited works originate from quantitative risk and economics journals but are increasingly cited by authors from behavioral and ethical subfields. This interplay is crucial for developing a comprehensive AML framework that simultaneously considers systemic vulnerabilities and agent-based manipulation. However, Figure 3's explanatory value is fully realized when combined with Figure 20 (the co-citation network diagram). The dendrogram shows how authors cluster around key conceptual terms, revealing thematic focus and disciplinary orientation (Hassan and Duarte, 2024), while the co-citation analysis in Figure 20 illustrates the placement of these authors within the broader citation ecosystem. This correspondence between thematic structure and citation behavior suggests that influence within the field depends not only on productivity or thematic relevance but also on referential centrality. Together, these diagrams form a dual lens through which to understand the disciplinary architecture of insurance fraud research: one based on semantic proximity and the other on cognitive sources.

Figure 4
Most Relevant Sources

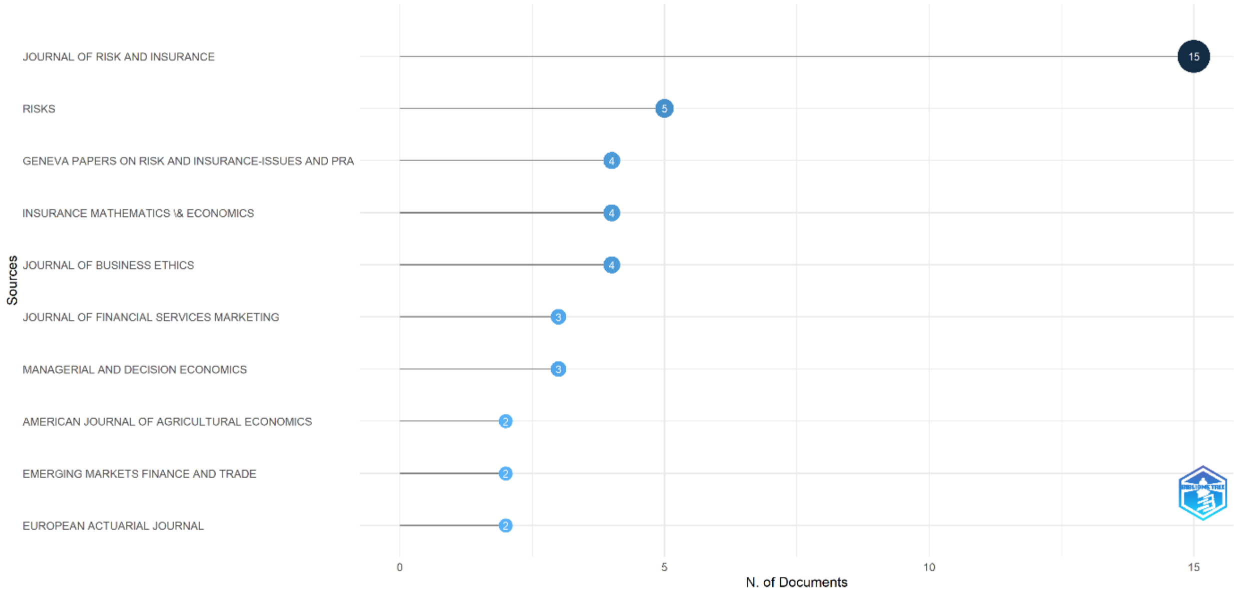


Figure 4 shows the primary sources of the articles. With 15 publications, the Journal of Risk and Insurance is the leading academic publisher for articles on money laundering in the insurance industry. Journals such as Risks (5 publications), Geneva Papers on Risk and Insurance - Issues and Practice (4 publications), Insurance: Mathematics and Economics (4 publications), Journal of Business Ethics (4 publications), Journal of Financial Services Marketing (3 publications), and Management and Decision Economics (3 publications) also feature prominently in Figure 4.

The composition of these journals demonstrates the field's position at the intersection of technical actuarial analysis, ethical discourse, and industry-specific financial marketing. The Journal of Risk and Insurance's dominance underscores the central role of risk modeling, actuarial valuation, and quantitative fraud assessment in the early academic formation of this topic. Conversely, the emergence of the Journal of Business Ethics suggests a growing shift in research toward behavioral and normative dimensions—a reflection of a growing understanding that insurance fraud is not simply a technological malfunction but rather an ethical failure rooted in corporate culture and incentive structures.

This proliferation of journals reflects a fragmented yet rich epistemological foundation, in which no single disciplinary perspective dominates. The field's deep roots in both hard fields (e.g., actuarial science, econometrics) and soft fields (e.g., ethics, governance) reflect the complexity of insurance money laundering: a phenomenon that simultaneously involves technical, regulatory, psychological, and institutional dimensions. The inclusion of journals such as Emerging Markets Finance & Trade or the American Journal of Agricultural Economics, albeit less frequently, also suggests that case studies from specific regions or industries (e.g., agricultural insurance fraud) are enriching the body of knowledge.

Figure 5

Sources Production over Time

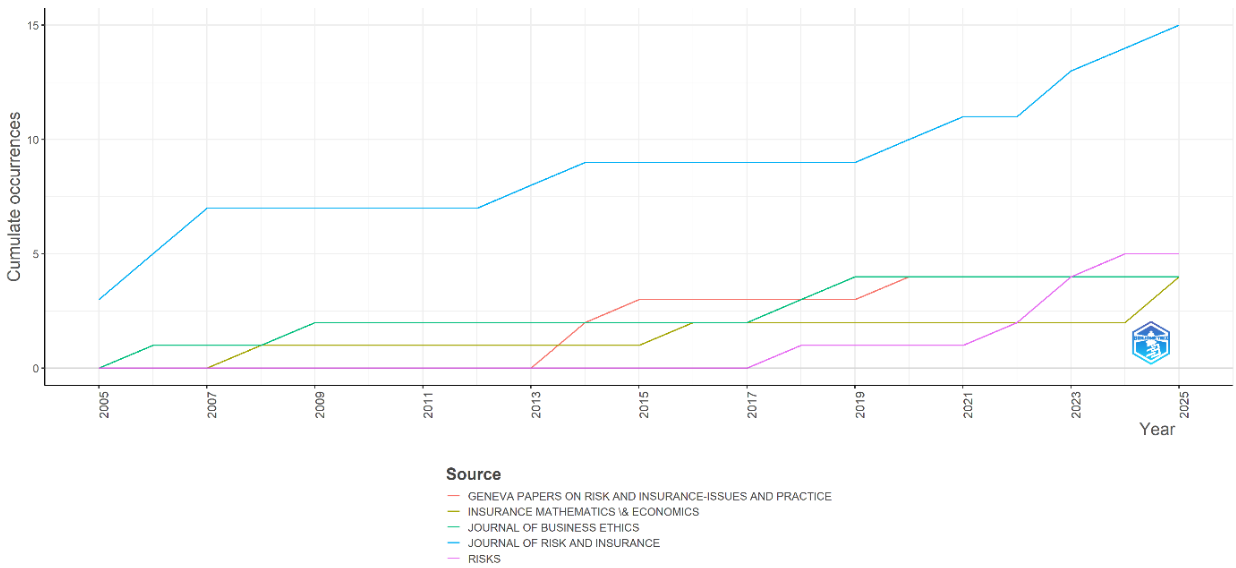


Figure 5 shows trends in source output over time to highlight the evolution of scholarly research. The temporal layering of journal articles reveals distinct epistemological trajectories. The sustained early dominance of the Journal of Risk and Insurance suggests the field's roots in actuarial science and quantitative risk modeling. This corroborates the theory that the technical problem of insurance fraud detection was initially considered to be amenable to statistical analysis (Bolton and Hand, 2002). However, the subsequent increase in the Journal of Business Ethics and the Journal of Financial Services Marketing demonstrates a paradigm shift: money laundering is now more commonly understood through the lens of behavioral ethics, organizational culture, and consumer choice. This expansion concords with shifts in regulation that focus on both compliance and the ethical behavior and reputation of financial institutions.

The anomalous growth patterns of journals like Risk and the Geneva Papers may be attributed to external causes, such as the recommendations of FATF, the high-profile scandals, or the digital revolution. These causes have a tendency to trigger a research boom in the short or long term. While significant, these sporadic contributions also demonstrate the field's significant reliance on legal or regulatory concerns during times of crisis.

Figures 4 and 5 not only show which journals have the greatest amount of influence in the field, but also how their contributions have changed over time. Figure 4 demonstrates that the Journal of Risk and Insurance is the most productive source of all, while Figure 5 shows that its output has increased over the past two decades.In contrast, other journals, such as the Journal of Business Ethics and the Journal of Financial Services Marketing, have recently seen increased participation, suggesting a shift in research paradigms from actuarial models to behavioral and reputational dimensions. This contrast reflects the field's maturation, moving from technical testing approaches to interdisciplinary analysis of ethical differentiation.

Figure 6
Most Relevant Affiliations

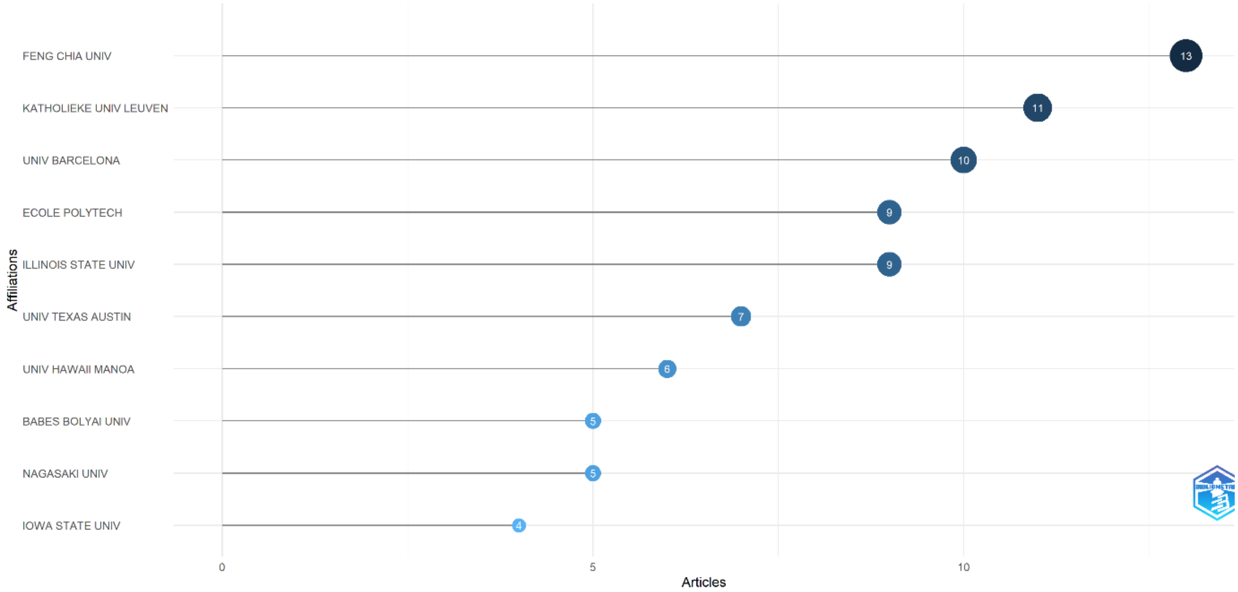


Figure 6 shows the scientific contributions of various universities and institutions, measured by the number of papers published on fraud and insurance research. Feng Chia University in Taiwan is the leading institution, with 13 papers: followed by the Catholic University of Louvain in Belgium, with 11. Other institutions include the University of Barcelona in Spain (10 papers); the École Polytechnique in France and the University of Illinois in the United States (9 papers each); the University of Texas at Austin in the United States (7 papers); and the University of Hawaii at Manoa in the United States (6 papers). These institutions are followed by the Babes-Bolyai University in Romania (5 papers); Nagasaki University in Japan (5 papers); and Iowa State University in the United States (4 papers).

This institutional distribution reveals not only geographic dispersion but also epistemic asymmetry. The dominance of institutions such as Feng Chia University, the Catholic University of Louvain, and the University of Barcelona suggests that intellectual leadership in money laundering and insurance research is not confined to traditional leading Anglo-American universities. Rather, it reflects a more polycentric academic structure, with institutions in both Western Europe and East Asia contributing diverse thematic and methodological insights. For example, East Asian universities often focus on data-driven and actuarial modeling, while European universities emphasize regulatory design and behavioral compliance.

In terms of knowledge output, these institutions are not only contributors but are also thematic hubs—organizing research clusters around dominant paradigms such as ethical misconduct, detection algorithms, or systemic vulnerabilities. Therefore, Figure 6 provides more than just an institutional ranking; it provides a visual representation of the structure of academic influence and the structural dispersion of fraud-related insurance research.

Figure 7

Affiliations' Production over Time

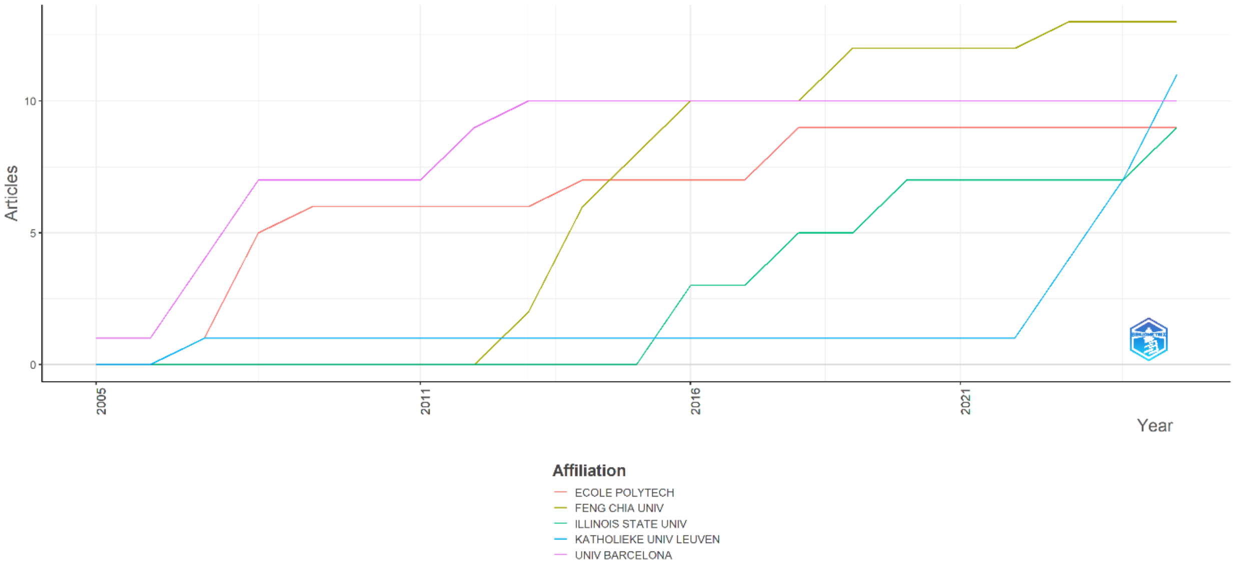


Figure 7 analyzes the publishing performance of the five top universities as provided in Figure 6. The colored chart shows trends from 2005 to 2025. It highlights the temporal nature of institutional engagement in insurance-related AML research. Publication output varies widely. Some institutions, such as the Catholic University of Louvain and Feng Chia University, experienced significant growth in certain periods, particularly after 2015. This suggests sporadic but intensive research mobilization, potentially driven by targeted funding programs, regulatory reforms, or strategic partnerships. However, other institutions, such as the École Polytechnique and the University of Barcelona, exhibit more stable performance over time, reflecting a pattern of sustained intellectual investment, likely underpinned by long-standing research centers or doctoral networks.

Figure 8

Geographic Distribution of Scientific Output

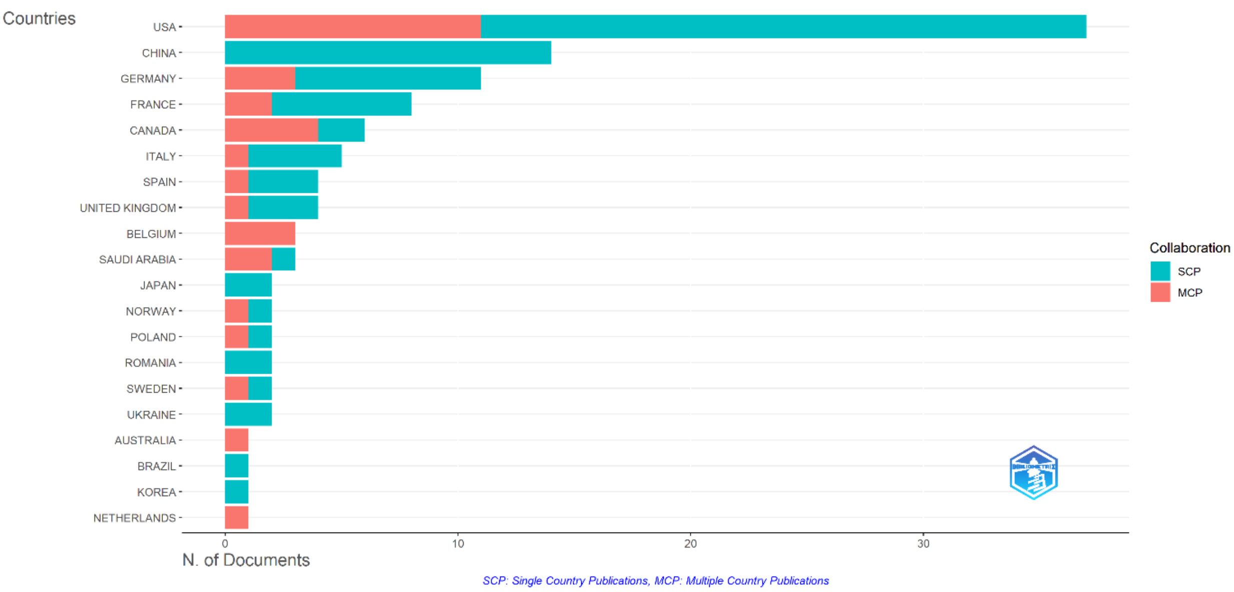


Figure 8 shows a geographic analysis of corresponding authors which highlights patterns in research productivity and collaboration. In other words, it reflects the spatial structure of knowledge output in the field. The figure includes both multi-country publication (MCP) rates and single-country publication (SCP) rates. MCP reflects the degree of international collaboration, while SCP represents the breadth of a country's research profile.

Of the 20 countries listed, the United States is considered the most productive, publishing 37 papers. This is likely due to its strong national research agenda in the fields of AML and insurance, as well as strong institutional support and a mature academic structure. The United States' MCP rate is approximately 29.7%, indicating a preference for a state-led research agenda with limited international collaboration. China, while second with 14 publications, has no MCPs. In other words, all articles published in China are SCPs, highlighting a nationalized research agenda, where discussions on AML and insurance are primarily influenced by domestic regulatory frameworks, national funding structures, and strategic divisions. Japan, Romania, Brazil, and South Korea, like China, all have MCP rates of 0%.

In contrast, countries such as Belgium, Australia, and the Netherlands have received more attention for their transnational research efforts, with MCP rates reaching 100%. These countries with high MCP rates act as transnational intermediaries, facilitating cross-border knowledge flows and playing a key role in translating local insights into globally relevant frameworks. This may be due to their strategic orientations or limited research infrastructure. Since research on these countries is scarce, the results may also be misleading.

Germany and France have a lower MCP rate of 27.3% and 25%, respectively, which suggests that their research outputs are balanced in relation to the amount of domestic research and international collaboration. On the other hand, Canada has a MCP of 66.7%, which is greater than the average MCP of 43.8% globally. This suggests that international research collaboration is more significant in this area. This asymmetry suggests a larger "central-periphery" dynamic within the research landscape. Countries with strong domestic publication capacity but limited international collaboration may exhibit a more nationally concentrated research profile. Conversely, smaller or less developed research systems that have a strong collaboration typically function as hubs that enhance the discussion of research by including multiple, context-specific perspectives. Specifically, the lack of or marginalization of countries in the South global community, such as Sub-Saharan Africa or Southeast Asia, in the research landscape is indicative of a structural exclusion that is not derived from a lack of relevance, but instead from barriers to accessing publications, funding, and language.

More broadly, the research data reveals how different countries' research priorities, capacities, and institutional structures influence scientific output. Well-funded countries with broad research areas, such as the United States and China, can generate domestic research output. On the other hand, smaller countries with limited resources and financial capacity are more likely to rely on international collaboration. However, this analysis has limitations. The dataset is limited to publications in English indexed in the WoS database. Therefore, significant works from other regions of the world, written in other languages, or indexed in other databases may be excluded. Therefore, the patterns identified should be considered indicative rather than definitive.

Figure 9
Country Production Over Time

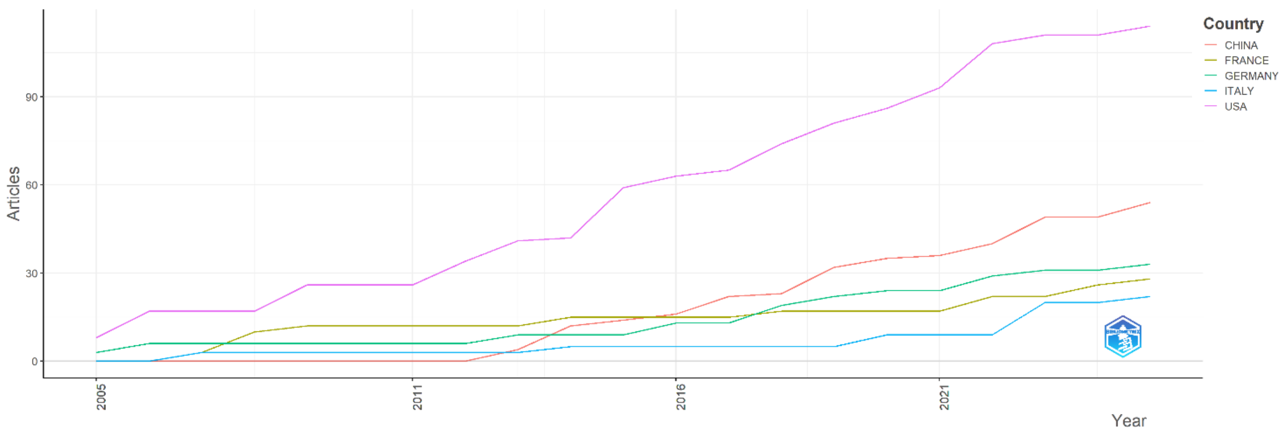
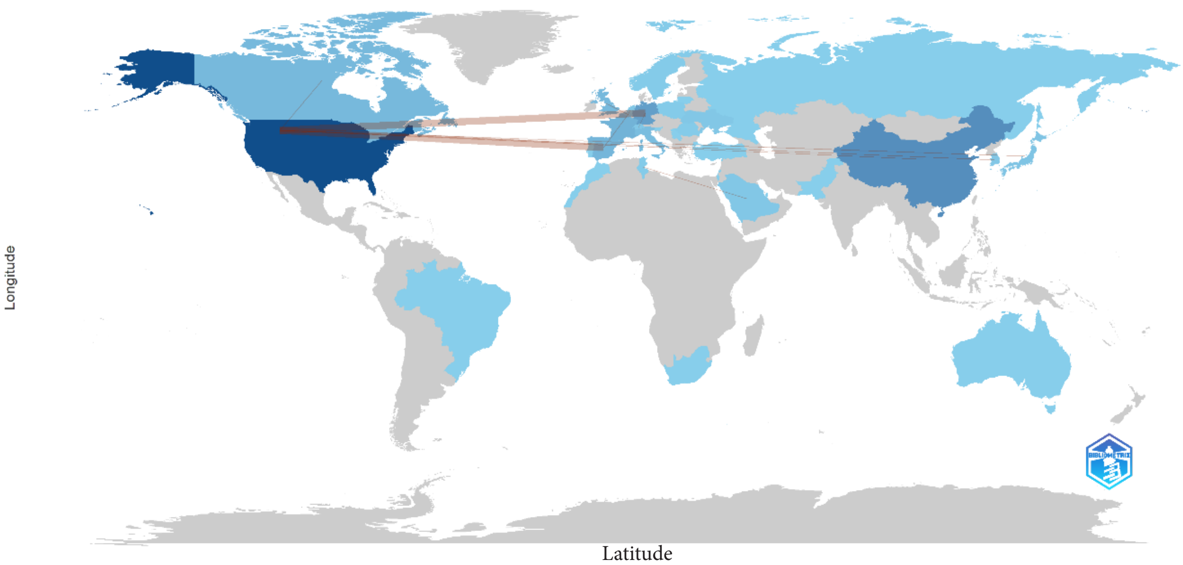


Figure 9 uses a colored line chart to illustrate the evolution of academic output over the years for the five leading countries shown in Figure 8. It reflects not only shifts in research intensity but also the dynamic interplay between regulatory developments, risk management paradigms, and cognitive focus across jurisdictions. The United States exhibited a clear upward trend in 2021, with a significantly higher growth rate than other countries. This is consistent with the institutional aftermath of the 2008 global financial crisis, which led to a greater emphasis on financial compliance, governance reform, and a reorientation of risk perception within the insurance industry. The Dodd-Frank Act (2010) and increased FATF assessments have shifted the research agenda, increasing attention to AML in previously marginalized sectors such as the insurance industry.

China's steadily upward trend is not only numerically significant but also methodologically illuminating. Its inward-looking publication pattern (see Figure 8) coupled with steady growth suggests that China is pursuing a national research strategy that is both politically driven and academically expansive yet structurally disconnected from the global AML debate. Unlike the United States, where the publication boom appears to have coincided with shifts in international discourse, China's rise may be associated with the synchronicity of domestic politics, including the introduction of national AML guidelines for insurers after 2013.

However, publication output in France, Germany, and Italy has developed more modestly, showing either flat or gradually increasing trends. This may indicate a mature but saturated research field, with incremental contributions limited by structural funding constraints or a shift in academic focus to emerging topics such as digital finance or ESG governance. The turning point around 2010 marks not only a quantitative acceleration in the literature but also a qualitative shift—a shift from descriptive analysis of insurance fraud to more integrated, risk-based, and compliance-focused research aligned with global standards.

Figure 10
Country Collaboration Map



The Country Collaboration Map in Figure 10 depicts the geographic and relational dimensions of the AML and insurance research landscape, reflecting cognitive hierarchies and institutional asymmetries. The United States, highlighted by the darkest shade of blue, stands out as a central hub for AML scholarship on the insurance industry, a finding that confirms previous research. China ranks second, highlighting its growing interest in financial crime prevention and insurance regulation. Significant clusters of publications also exist in Eastern Europe, particularly in the United Kingdom, Germany, France, and Italy.

The United States dominates transnational co-authorship networks, passing its regulatory logic and methodological preferences across the academic landscape. This structural centrality not only ensures research visibility but also shapes the normative assumptions underlying global money laundering research. Continued partnerships with Western European countries (particularly Germany, France, and Italy) demonstrate that the Euro-Atlantic institutional ecosystem continues to define the paradigms of compliance, risk management, and financial regulation. While bilateral ties exist between China and the United States, this does not necessarily imply symmetry. Rather, it reflects the strategic tension between two competing regulatory models: China's state-led, state-centric approach to compliance and the market-oriented, disclosure-focused American framework. China's presence as a co-drafting partner does not negate its relative isolation in regulatory influence, as evidenced by the lack of multilateral collaboration with other regions.

The marginal representation of countries in the Global South (particularly Africa and South America) suggests that specific regional vulnerabilities remain excluded from mainstream AML discourse. Despite significant illicit financial flow (IFF) risks, these regions remain cognitively marginalized. This absence is more than a statistical observation; it represents a structural blind spot that undermines the global applicability of the AML governance framework.

The findings highlight the dominance of high-income industrialized countries in the research landscape, while developing and emerging economies remain significantly underrepresented, despite facing growing risks from illicit financial activities and systemic vulnerabilities. Consequently, more inclusive and globally representative research projects are needed to address region-specific risks, regulatory frameworks, and capacity constraints.

Figures 8 and 10, taken together, highlight the structural asymmetry between geographic concentration and collaborative inclusiveness. Figure 8 shows the dominance of the United States and China in terms of publication volume, while Figure 10 highlights their significantly lower share of international collaboration compared to smaller countries such as Belgium and the Netherlands. This disparity highlights a center-periphery dynamic, whereby epistemic power remains concentrated, but cross-border dialogue is increasingly driven by less effective but internationally connected actors. This pattern underscores the need for broader collaboration to avoid regional epistemic silos.

Figure 11
Most Relevant Words

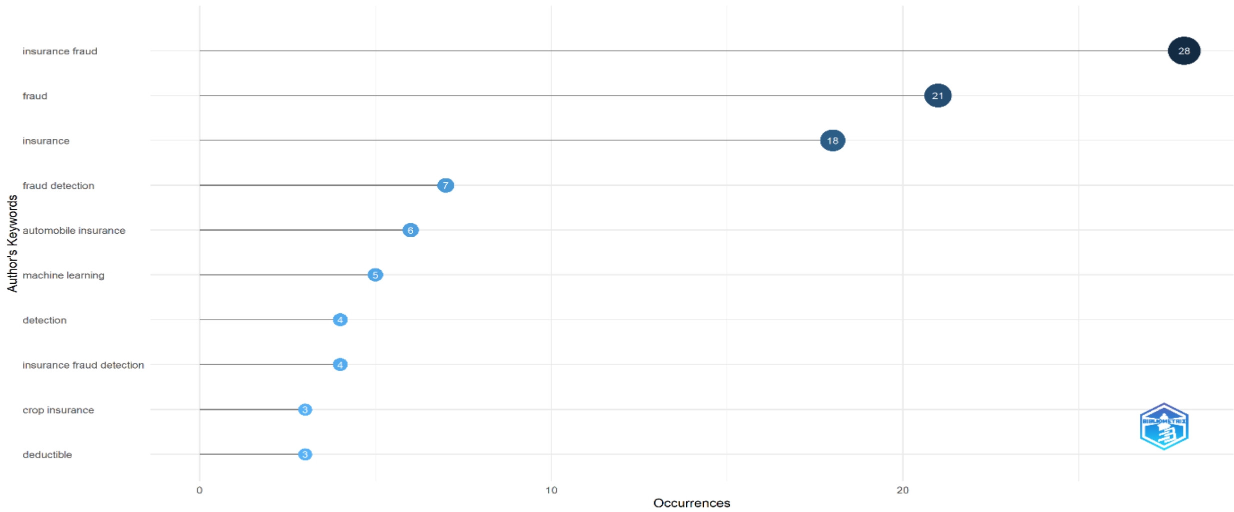
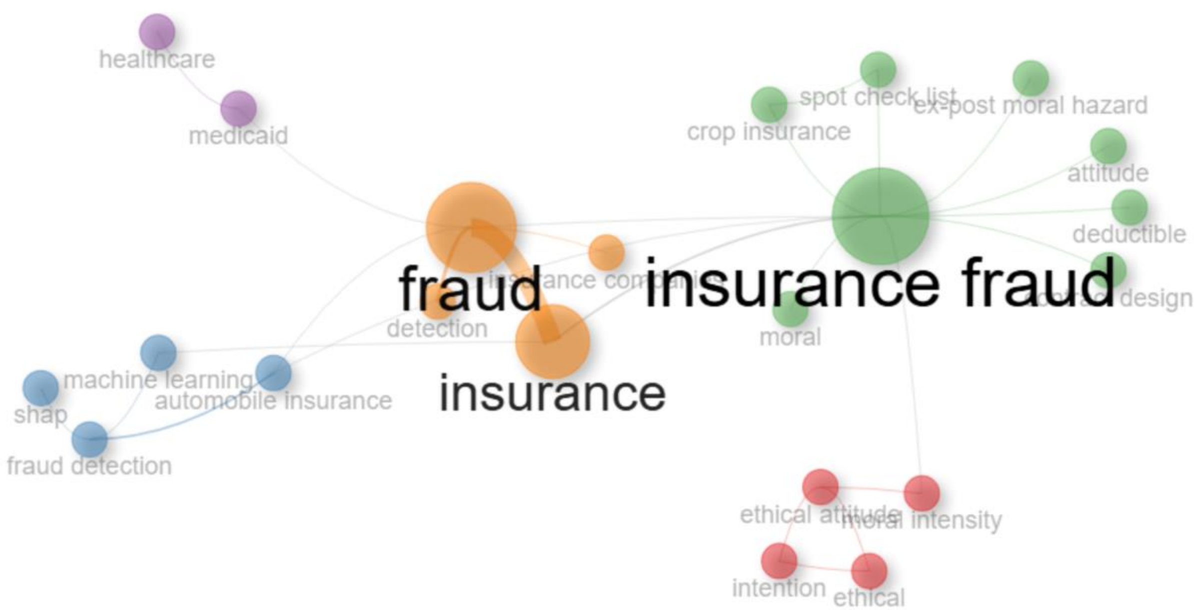


Figure 12
Word Clouds

The visualizations in Figures 11 and 12 display the most relevant keywords and word clouds generated from the authors' keywords, providing a semantic overview of the thematic orientations within the literature. As expected, keywords such as "insurance fraud," "fraud," and "insurance" dominate, reflecting the field's core conceptual foundation. However, the prominence of terms such as "fraud detection," "machine learning," and "motor vehicle insurance" suggests that research is shifting away from traditional regulatory and policy-centric narratives toward more technical and analytical areas. This evolving vocabulary reveals the interdisciplinary nature of the research, which increasingly draws on computational methods as well as economic and ethical considerations. Overall, the thematic convergences and divergences observed within these concepts suggest that the literature is moving toward a multi-layered epistemological structure that balances policy relevance, algorithmic modeling, and behavioral risk.

Figure 13
Co-Occurrence Network



The keyword co-occurrence network shown in Figure 13 is crucial for identifying the frequency of common use of certain keywords within the literature. Co-occurrence across multiple studies can be interpreted as a sign of conceptual relationships or shared research focus (Bornmann et al., 2018). Figure 13 identifies five distinct clusters, where keywords are interconnected to form specific thematic areas. Each node represents a keyword, and its size reflects its frequency. The keywords “fraud,” “insurance fraud,” and “insurance,” identified in Figure 11, are also considered central to this network because they play a significant role in nearly all research areas in the dataset.

The orange cluster, containing the keywords “fraud,” “insurance,” and “fraud detection” as anchors, represents a thematic focus on the operational and institutional aspects of fraud prevention within the industry. The inclusion of the keywords “insurance company” and “detection” is crucial for identifying and mitigating fraudulent activity. Thus, there is an intersection between applied research and institutional concerns, connecting insurance fraud with risk management and regulatory compliance.

The green cluster has the term “insurance fraud” as its primary keyword. It additionally includes keywords that are specific to the context, such as “crop insurance”, “sampling audit”, “ex post moral hazard”, “attitude”, and “design.” This cluster is dedicated to studies that involves the development of policies and the prevention of fraudulent behavior in the insurance industry. These specific keywords also suggest a focus on recognizing and preventing fraud through monitoring and verification processes. Conversely, the presence of keywords like “ex post moral hazard” and “attitude” suggests that the research in this cluster is concerned with the psychological and economic causes of illegal behavior. In other words, this cluster combines behavioral components with institutional components and specific industry policy assessments. By including the word “design” in the cluster’s name, the research within the cluster not only provides diagnoses, but also explores preventative strategies for addressing fraud-related issues.

The blue cluster, which is organized around keywords like “machine learning,” “automobile insurance,” and “fraud detection,” is dedicated to the technology and artificial intelligence in this field. The size and significance of the “motor insurance” component suggests that this sector is a significant testing ground for machine-learning applications. This is attributed to large amount of claims data and obvious patterns of fraud. Overall, this cluster demonstrates the increasing association between insurance analytics, artificial intelligence, and regulation, which makes it significant in the center of innovation.

Research within the red cluster shifts its focus from external detection mechanisms to exploring the internal behavioral and psychological causes of misconduct. Key keywords are “morality,” “moral attitudes,” “intention,” and “intensity.” This cluster’s thematic research area explores how individuals’ moral, ethical, and psychological dispositions influence their potential for fraudulent behavior. Therefore, the focus is on how and why individuals rationalize unethical behavior, particularly in the insurance industry. This cluster integrates behavioral science, criminology, and organizational ethics.

The final cluster, the purple cluster, contains the keywords “healthcare” and “Medicaid,” which point to a very specific area of fraud within the health insurance system. Research within this cluster reflects growing concern about the system’s vulnerabilities and inefficiencies, which make health insurance and related programs highly susceptible to abuse. The inclusion of the keyword “Medicaid” indicates that research within this cluster is primarily concentrated in the United States, given its high level of funding and complex administrative structure. These factors provide a necessary foundation for scientific interest in fraud-related research. The relevance of this research is particularly important for policymaking, as health care fraud not only results in economic losses but also undermines public trust and leads to the misuse of resources. Therefore, the purple cluster connects policy analysis with health economics and regulatory frameworks.

Figure 14

Words' Frequency over Time

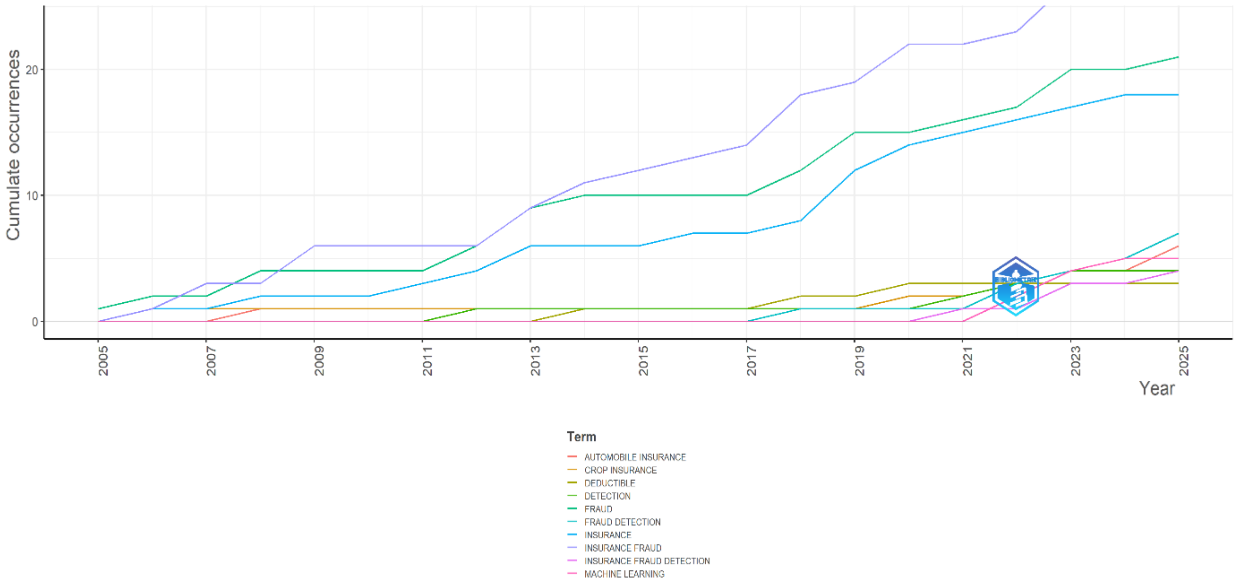


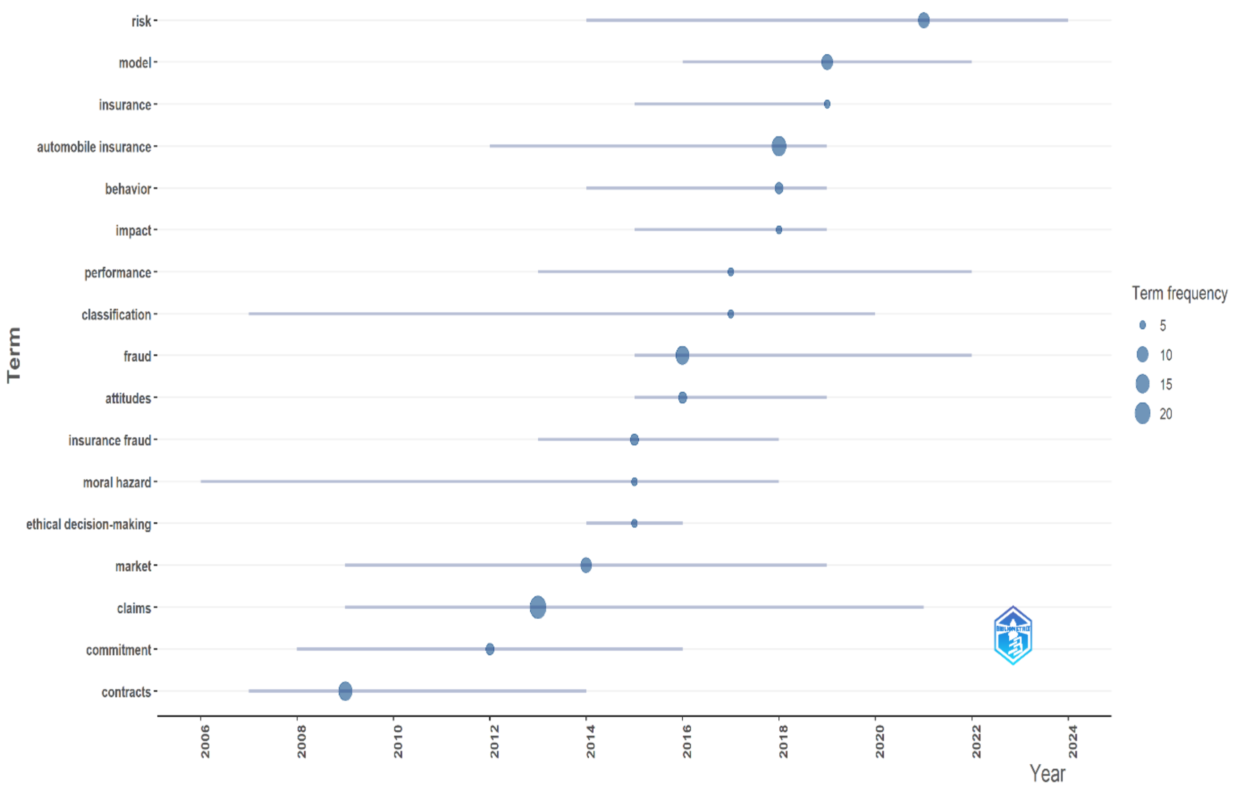
Figure 14 presents a line chart of keyword usage frequency from 2005 to 2025. Each colored line represents a specific keyword, ranging from general terms (e.g., insurance, fraud) to more specialized terms (e.g., auto insurance, insurance fraud detection, machine learning). This visualization not only provides insight into the evolving research agenda but also reveals the progress of new technological paradigms entering the field.

The most striking trend is the significant and sustained growth in the use of keywords such as "insurance," "insurance fraud," and "insurance fraud detection," particularly after 2015. This indicates a significant increase in academic attention to fraud-related risks in the insurance system, consistent with global regulatory changes, the digitization of the claims process, and increased data availability. The accelerated growth observed after 2020 suggests a further convergence of academic, technical, and policy-driven interest in this field.

In contrast, popular terms such as "crop insurance", "deductible", and "automobile insurance" have experienced slower but more stable growth, reflecting their more niche or application-specific research trajectories. The rise of "machine learning" as a buzzword since the late 2010s indicates a paradigm shift in research toward data-driven approaches and the integration of artificial intelligence into fraud detection systems. The increasing adoption of machine learning reflects a broader transformation in financial technology and analytics-based risk mitigation strategies.

The observed patterns highlight two key dynamics in the literature: (1) the consolidation of core concerns around "fraud" and "insurance fraud", which have laid the institutional and conceptual foundations of the research field; and (2) the diversification of methods and application contexts, particularly through the increasing use of technological tools and behavioral insights. Taken together, these dynamics suggest that the field is evolving from a compliance-centric discourse to one that integrates algorithmic intelligence, behavioral theory, and industry complexity.

Figure 15
Trend Topics



The distribution of research areas and topics was further analyzed using a Trend Topics graph. The frequency of the most commonly used keywords, determined from the ID field of WoS database records, is presented by publication year. The size of the circle indicates the frequency of the term in the corresponding year, while the horizontal bar represents the interquartile range of the frequency, indicating whether the term's change over time is consistent or volatile. This approach allows identification of persistent core themes and emerging conceptual anchors in the literature.

The graph shows patterns that explain the way in which academic interest in AML has evolved over time with regard to insurance. Constantly occurring keywords like “insurance”, “insurance fraud”, “automobile insurance”, and “claims” demonstrate the structural pillars of the field as well as the continued importance of specific topics. Their long-standing nature suggests that these ideas represent the foundational concepts of more specialized or innovative research questions. Meanwhile, keywords like “risk”, “model”, and “behavior” have become more frequently employed, this is particularly true of them since 2016. This indicates a shift in the paradigm of detection and prevention of fraud towards more analytical, sensitive, and behavior-based approaches.

This transition parallels a larger epistemological shift in the field: a shift away from the conventional and institutional perspective (e.g., “contracts”, “ commitment”) that were the dominant themes in earlier literature toward a more empirical and computational approach. The early focus on the legal and procedural aspects of insurance transactions has been augmented or replaced by numerical models, behavioral studies, and performance evaluations. This is particularly apparent in the emergence of classes of terms like “ classification”, “ performance”, and “ impact”, which demonstrate an increasing interest in evaluating the operational effectiveness and power of fraud detection systems.

Additionally, the recent increase in the prevalence of “moral hazard”, “ethical decision-making”, and “attitudes” has increased the prevalence of behavioral finance and moral psychology in the literature. These additions demonstrate a complex perspective that covers both technical issues and behavioral issues associated with insurance fraud.

Figure 16

Thematic Evolution Map

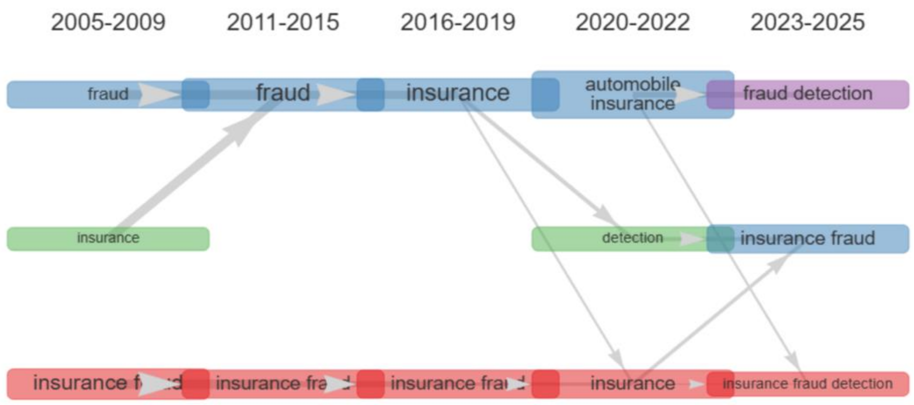


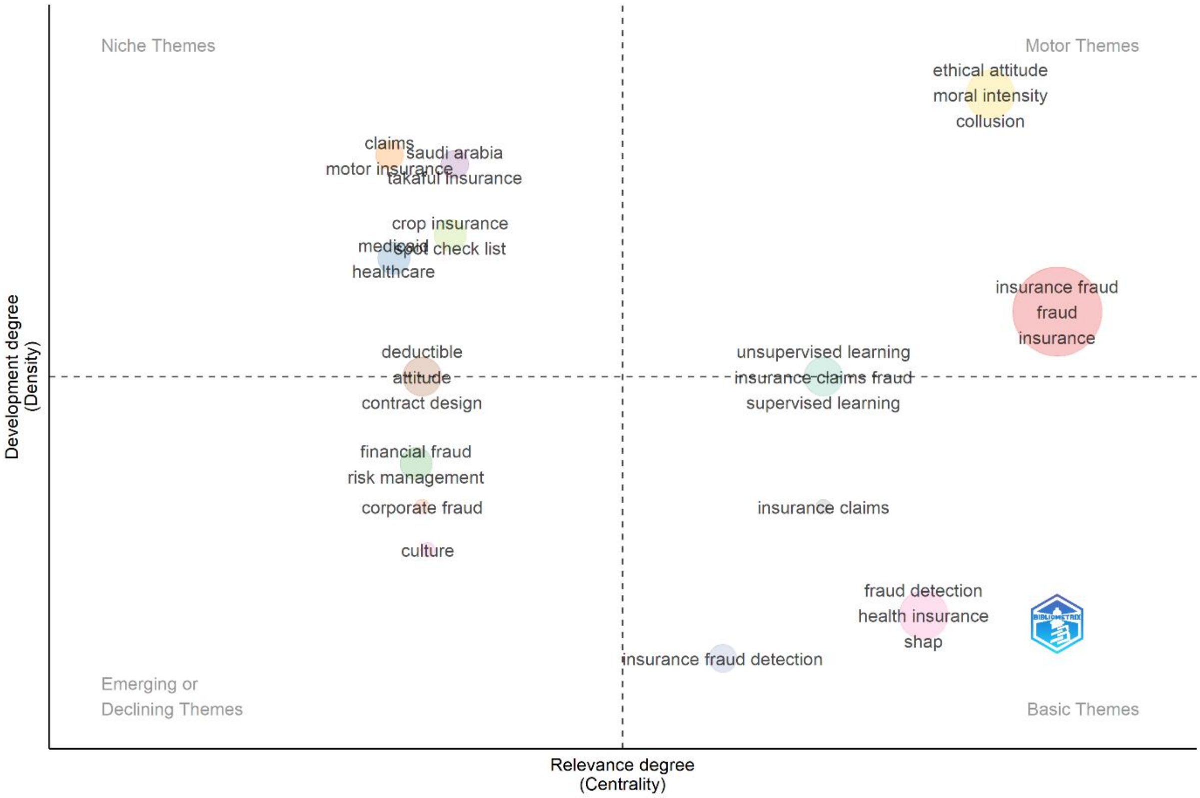
Figure 16 illustrates the progression of topics and the influence they have on one another between 2005 and 2025. The time period from 2005 to 2009 is considered an early stage, where the topic of "fraud" was the most popular. In 2011 and 2015, the words "fraud" and "insurance" started to converge. Starting in 2016, the topic of "insurance" has increased in importance and is now more specialized with the emergence of the term "automobile insurance" in 2019. This shift in the theme is indicative of the field's increasing complexity: from a basic discussion of fraud to the prevention of specific types of fraud within the insurance field.

From 2020-2022, the primary focus is on "automobile insurance". However, following 2020, the transition to "fraud detection" represents a significant change in perspective, machine learning, and algorithmic monitoring have become prevalent in the academic field. The division of topics into operational ("automobile insurance") and conceptual ("detection," "insurance fraud") areas also indicates an interdisciplinary approach to topics like risk management, behavioral analysis, and regulatory modeling. This increase in development suggests that the research ecosystem is increasingly composed of empirical, industry-specific, and policy-oriented findings.

Figures 15 and 16 depict not only the frequency of key research themes but also their semantic shifts over time. Figure 15 illustrates the temporal trajectory of specific keywords (such as "fraud detection" and "model"), while Figure 16 situates these trends within a broader thematic shift—from basic discussions of fraud to more detailed, sector-specific typologies, such as automobile insurance. This multi-layered depiction illustrates how the field has evolved from institutional analysis to a computational, industry-centric, and ethically anchored framework, reflecting broader changes in regulatory practices and digital technologies.

Figure 17

Thematic Map



The thematic map in Figure 17 strategically visualizes the literature through keyword co-occurrence analysis, aiding understanding of research topics. Identified topics are presented along two dimensions: centrality and density. Centrality indicates the relevance of a document to the overall research field and the scope of existing work, while density reflects its importance and degree of internal development. The four quadrants within these two dimensions are called motor themes, niche themes, emerging or declining themes, and basic themes (Saha et al., 2024).

The first quadrant, motor themes, features highly developed and interconnected topics due to their high centrality and density. These topics include keywords like “”insurance fraud”, “fraud”, “insurance”, “ethical attitude”, “moral intensity”, and “collusion”. These keywords exhibit a dual concern of research: on the structural nature of vulnerabilities, such as the utilization of insurance products for money laundering, as well as on the behavioral aspects, such as the ethical decision-making.

The second quadrant (niche themes) contains topics with a high concentration of niche attributes, including keywords like “claims”, “motor insurance”, “Saudi Arabia”,”Medicaid”, “healthcare”, and “crop insurance”. These topics that are specialized are important, but understudied. Despite their specialization and development, they still have a lack of connection to the mainstream literature. The low centrality in this quadrant may indicate the focus of research on specific countries or industries. The keyword “Saudi Arabia” is associated with local concern regarding AML and insurance.

The third quadrant in Figure 17 contains topics that are emerging or are declining, these topics have a low density and low centrality in the plot. Topics in this quadrant are either a potential future research endeavor or represent a decrease in the literature, thus having a low impact. This quadrant contains keywords like “financial fraud”, “risk management”, “corporate fraud”, and “ culture”, all of which have lost popularity in the AML and insurance fields.

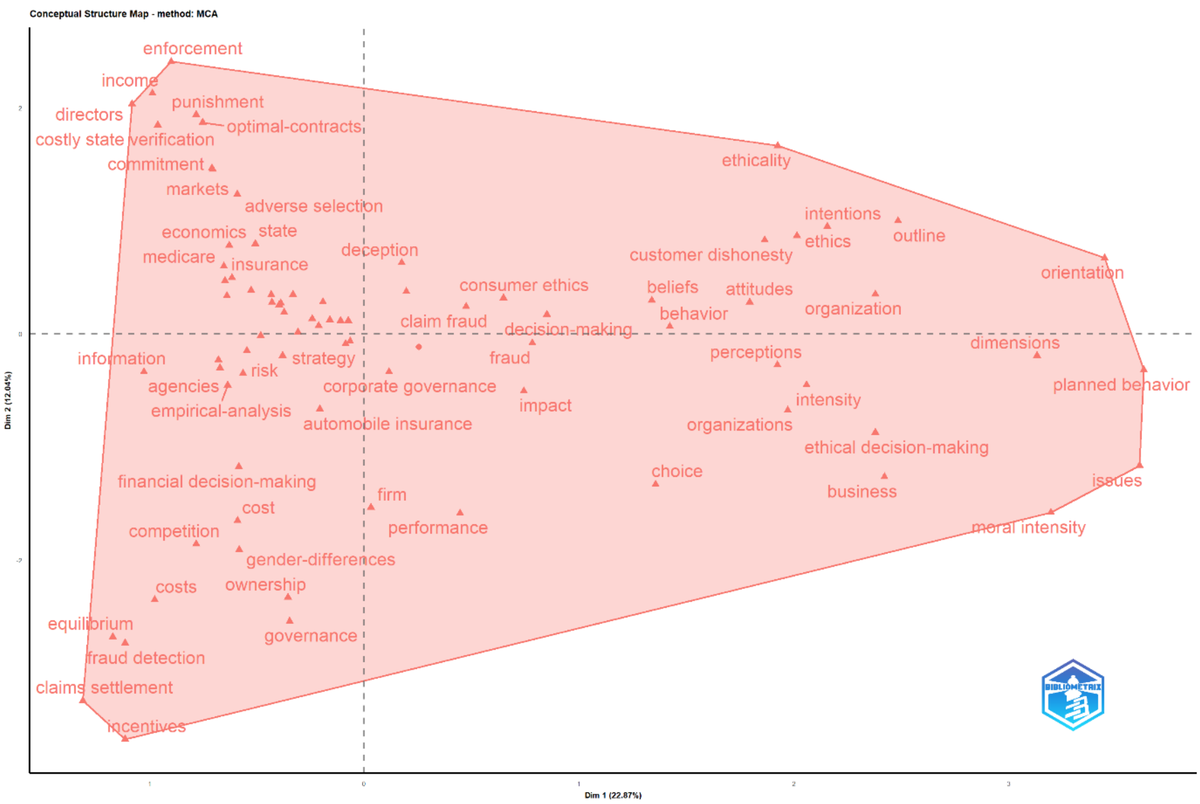
The fourth quadrant, basic themes, encompasses topics that are crucial to the literature but require further development. Keywords such as “insurance claims”, “insurance fraud detection”, “fraud detection”, “health insurance”, and “Shap” are examples of topics that contribute to the development of the field and require further attention.

This strategic mapping highlights the multidimensional nature of the field, where behavioral concepts such as “ethical attitude” and “moral intensity” are intertwined with operational nodes such as “insurance fraud” and “fraud detection.” Highly core concepts cluster clearly in the motor and basic quadrants, revealing a dichotomy in scientific focus: theoretically mature but behaviorally fragmented topics on the one hand, and technically foundational but methodologically underdeveloped fields on the other. Meanwhile, the presence of geographically restricted terms such as “Saudi Arabia” and “Medicaid” in the niche quadrant suggests a pressing need for cross-jurisdictional comparative research examining how national regulatory architectures coordinate insurance fraud typologies. Ultimately, this mapping requires an integrated research agenda that integrates ethical reasoning, algorithmic enforcement, and institutional design to combat insurance-related financial crime.

The thematic areas identified in Figure 17 build on the co-occurrence pattern visualized in Figure 13. Both figures depict a two-pronged discussion: structural and regulatory issues such as “fraud” and “insurance fraud” on the one hand, and emerging behavioral and ethical concepts such as “moral intensity” and “ ethical attitude” on the other. The convergence of these dimensions in the figures suggests a gradual shift in the field toward a fusion of algorithmic intelligence and ethical reasoning, highlighting the need for a hybrid AML framework that is both data-driven and normatively based.

Figure 18

Factorial Map



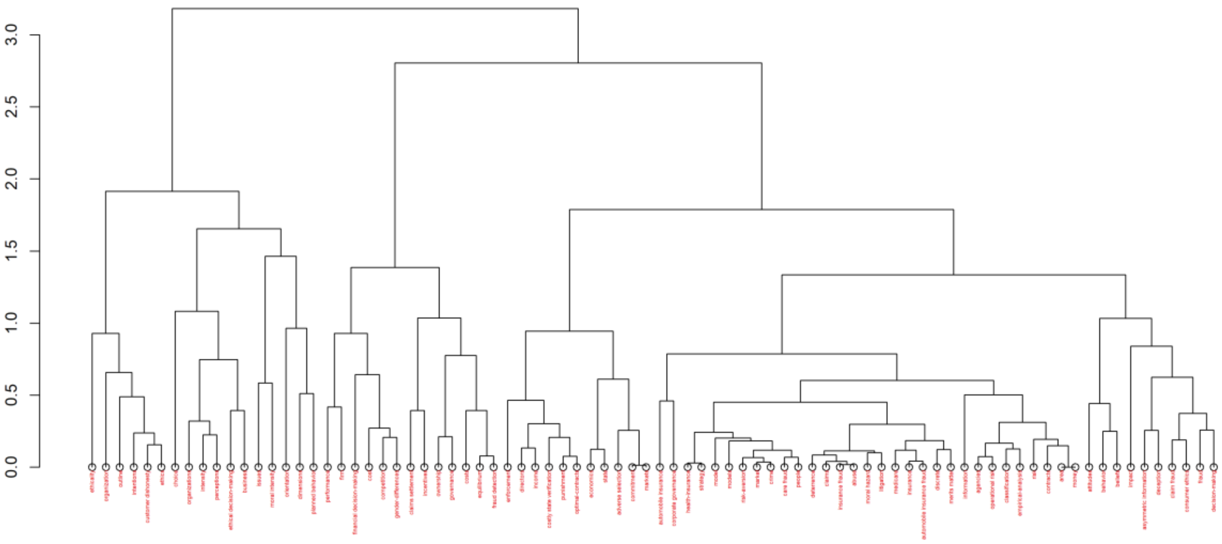
A Factorial Map also known as a Correspondence Map was created using Multiple Correspondence Analysis to visually depict the relationships between keywords. Figure 18 illustrates this graph. It depicts co-occurrence patterns in two dimensions and displays the relative distribution and distances between keywords, creating clusters of interconnected topics. In other words, keywords that frequently appear together in research are grouped together (Abhilash et al., 2022).

Keywords such as “fraud”, “punishment”, “income”, and “enforcement” are located close together, forming a cluster that reflects a research focus on regulation and deterrence. This cluster reflects the continued interest in enforcement mechanisms, sanctions, and financial incentives in the insurance industry, all designed to prevent fraud. The strong connections between keywords emphasize their conceptual alignment and their central importance in designing AML strategies.

Another distinct cluster contains keywords such as “corporate governance”, “financial decision-making”, “competition”, “risk”, and “equilibrium”. These studies share similarities with research in economics, management, and financial ethics, indicating a focus on organizational structures and market dynamics that influence fraud risk, ethical behavior, and institutional integrity. Another area of research encompassing “ethics”, “consumer ethics”, “ethical decision-making”, and “moral intensity” also reflects the growing importance of behavioral and moral dimensions. This area focuses on individual and societal responses to fraudulent behavior and their moral decision-making.

Figure 19

Factorial Map Dendrogram



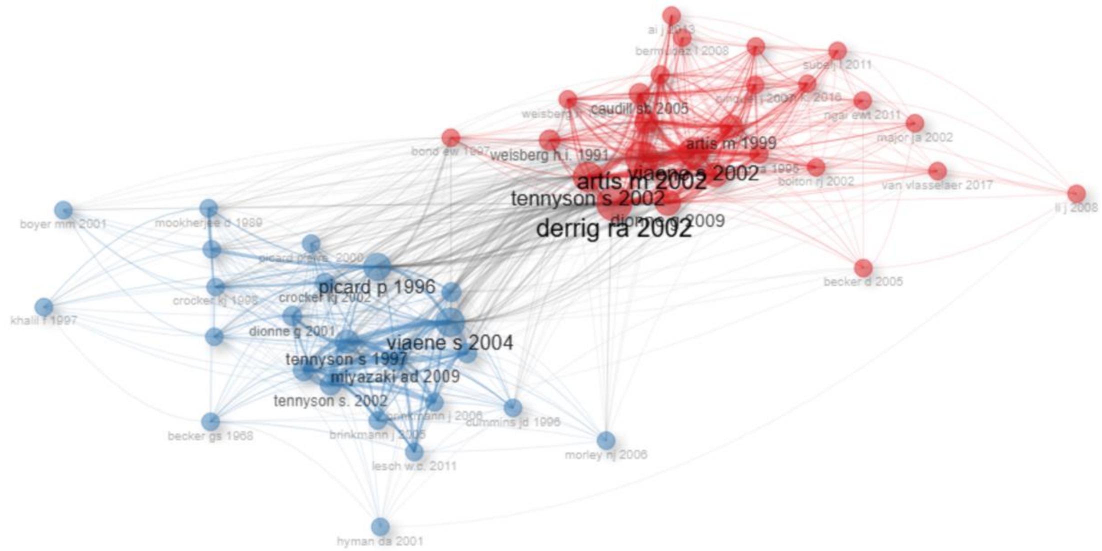
Hierarchical cluster analysis was used to further examine the conceptual structure of the research field. The resulting Factorial Map Dendrogram, shown in Figure 19, visually illustrates how keywords form clusters based on their thematic and semantic proximity. The vertical axis represents the similarity between keywords, while the horizontal axis represents the keywords themselves and their branches. The length of the branches indicates the similarity of the concepts. Shorter branches indicate closer conceptual relationships.

The dendrogram reveals certain thematic clusters. For example, one major node is composed of the keywords “fraud,” “insurance fraud,” “claims,” and “moral hazard,” reflecting a cross-disciplinary research focus based on criminology, behavioral economics, and actuarial science. Another node, composed of the keywords “corporate governance,” “financial decision-making,” and “competition,” integrates themes from finance and organizational theory. The focus is on the institutional and managerial aspects of AML, with a particular emphasis on ethical leadership, compliance systems, and decision-making frameworks in the insurance industry. Another prominent cluster contains the keywords “ethics,” “moral intensity,” and “consumer ethics.” The structure of this cluster emphasizes the relevance of ethics in the decision-making frameworks used by individuals and systems to address illicit financial activities.

The dendrogram not only demonstrates connections between concepts but also reveals hierarchical relationships between different research fields. The field is then broken down into several major research areas, ranging from technical risk models and contract theory to regulatory and ethical issues.

Figures 18 and 19 provide complementary perspectives on the field’s semantic architecture. The Factorial Map (Figure 18) identifies proximity between concepts based on multiple correspondence analysis, while the tree diagram in Figure 19 groups similar themes hierarchically, highlighting the underlying structural consistency between concepts such as “governance,” “moral hazard,” and “fraud.” Together, they map both horizontal (associative) and vertical (hierarchical) relationships, revealing the multifaceted complexity of AML insurance research and providing a roadmap for future conceptual integration.

Figure 20
Co-citation Network



The co-citation network shown in Figure 20 visualizes the citation patterns of literature on AML and insurance in the WoS database. It consists of nodes representing cited articles and edges representing co-citation links. The proximity of nodes indicates the frequency of co-citations and constitutes the scientific community of related topics. The closer the references in the network are to each other, the more frequently they are co-cited. Overall, two distinct clusters can be observed: red and blue. These clusters represent specific areas of conceptual development.

The red cluster primarily consists of studies by Derrig (2002), Artis et al. (1999; 2002), and Tennyson (2002), which focus on economic modeling, regulatory compliance, and insurance fraud. The blue cluster primarily consists of studies by Picard (1996), Viaene and Dedene (2004), and Miyazaki (2009), which focus on the operational aspects of risk modeling, predictive analytics, and fraud detection. The increase in citations since the early 2000s indicates that this research field is in a formative period of development. 2002 saw the highest number of studies, likely due to the impact of post-9/11 risk management reforms and the integration of data science techniques with fraud detection.

The citation patterns depicted in Figure 20 align with the intellectual structure depicted in Figure 3. Figure 3 demonstrates how author-descriptor-reference triplets form central conceptual pathways. Figure 20 further confirms this by mapping the co-citation clusters that underpin the field. Authors such as Derrig, Tennyson, and Picard not only appear frequently in citations but also form the cornerstone of the discipline's cohesion, connecting risk modeling with regulatory discourse. Together, these maps illuminate the field's genealogy and intellectual framework.

4. DISCUSSION

4.1. Main Findings

This bibliometric study provides a comprehensive overview of research on financial crime in the insurance sector, with a particular focus on money laundering and insurance fraud. The findings indicate that the literature has expanded gradually over the past two decades, although growth has been uneven and characterized by thematic fragmentation. Research activity is concentrated around several major themes, including fraud detection, behavioral ethics, regulatory compliance, industry-specific applications, and policy-related studies.

Keyword analyses and co-occurrence networks reveal a growing interest in technology-based approaches to fraud detection. Terms such as "machine learning," "fraud detection," and "automobile insurance" have become increasingly prominent in recent years. At the same time, behavioral concepts such as "ethical attitude," "moral intensity," and "collusion" continue to appear within the literature, suggesting that researchers increasingly recognize the importance of human and organizational factors alongside technological solutions.

The findings also demonstrate that the literature remains fragmented across journals, institutions, and countries. While certain journals and institutions have emerged as leading contributors, no single theoretical or methodological framework dominates the field. This pattern is consistent with the interdisciplinary nature of financial crime research, which draws upon insurance studies, finance, economics, criminology, information systems, and regulatory governance.

4.2. Theoretical Implications

The thematic clusters identified in the analysis can be interpreted through the theoretical perspectives introduced in this study. The behavioral ethics cluster aligns closely with behavioral economics and Fraud Triangle Theory, emphasizing the role of incentives, rationalization, and opportunity in fraudulent behavior. Similarly, the regulatory compliance cluster reflects institutional and regulatory governance perspectives, highlighting the importance of formal rules, supervisory mechanisms, and organizational structures in shaping compliance outcomes.

These findings suggest that financial crime in the insurance sector should not be viewed solely as a technical or operational issue. Instead, it represents a multidimensional phenomenon shaped by technological, behavioral, institutional, and regulatory factors. The coexistence of technological and behavioral themes within the literature further supports the need for interdisciplinary approaches to understanding and preventing financial crime.

4.3. Policy Implications

The results also carry important implications for regulators and insurance practitioners. Despite the growing importance of anti-money laundering (AML) measures in the insurance industry, AML-specific themes remain less visible than traditional insurance fraud topics. This finding suggests that the insurance sector continues to be examined primarily from a fraud prevention perspective rather than through a broader AML/CFT framework.

International standards such as FATF Recommendation 1 and IAIS Insurance Core Principle 22 emphasize the importance of risk-based supervision, customer due diligence, beneficial ownership transparency, and continuous monitoring of high-risk insurance products. The findings indicate that these issues remain relatively underrepresented within the academic literature. Therefore, greater integration between fraud detection research and AML/CFT policy discussions may contribute to a more comprehensive understanding of financial crime risks in the insurance industry.

4.4. Limitations and Future Research

Several limitations should be acknowledged. First, the analysis is restricted to English-language publications indexed in the Web of Science Core Collection. Consequently, relevant studies published in other languages or indexed in alternative databases may not be captured. Second, bibliometric methods provide insights into publication patterns and knowledge structures but do not directly evaluate the quality or empirical validity of individual studies.

Future research may expand the scope of analysis by incorporating Scopus and other bibliographic databases. Additional studies could also focus more directly on AML-specific issues in the insurance industry, including risk-based supervision, AML cost-effectiveness, beneficial ownership transparency, and the interaction between AML/CFT requirements and insurance regulatory frameworks such as Solvency II and IAIS standards. Furthermore, comparative studies examining differences across jurisdictions may improve understanding of how regulatory environments influence financial crime prevention strategies.

5. CONCLUSION

This study maps the intellectual structure and thematic development of research on financial crime in the insurance sector. The findings reveal a growing body of literature characterized by increasing interest in technology-based fraud detection methods, alongside continued attention to behavioral and regulatory dimensions of financial crime.

The results indicate that while significant progress has been made in developing analytical and technological approaches to fraud detection, AML-specific issues remain comparatively underexplored within the insurance literature. The findings also demonstrate that insurance fraud and money laundering constitute related but conceptually distinct domains within the broader financial crime literature. Greater integration of regulatory, institutional, and behavioral perspectives may therefore strengthen future research and contribute to more effective financial crime prevention frameworks. Overall, this study provides a foundation for future investigations and offers a structured overview of the major trends, contributors, and research gaps shaping the field.

REFERENCES

Abhilash, Shenoy, S. S., & Shetty, D. K. (2022). A state-of-the-art overview of green bond markets: Evidence from technology empowered systematic literature review. Cogent Economics & Finance, 10(1), 2135834.

Acharya, S. (2015). Money Laundering (ML) and Terrorism Financing (TF) in the Insurance Market: A Risk and Vulnerability. Available at SSRN 2604560.

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: A survey on explainable artificial intelligence (XAI). IEEE Access, 6, 52138–52160. https://doi.org/10.1109/ACCESS.2018.2870052

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., … & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. Information Fusion, 58, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Artis, M., Ayuso, M., & Guillen, M. (1999). Modelling different types of automobile insurance fraud behaviour in the Spanish market. Insurance: Mathematics and Economics, 24(1-2), 67-81.

Artís, M., Ayuso, M., & Guillén, M. (2002). Detection of automobile insurance fraud with discrete choice models and misclassified claims. *Journal of Risk and Insurance*, 69(3), 325-340.

Bagaskara, F. F., & Yanti, H. B. (2025). Examining Money Laundering in the Insurance Industry Through Fraud Heptagon Theory Perspective. *Indonesian Interdisciplinary Journal of Sharia Economics (IIJSE)*, 8(2), 4703-4723.

Bhattacharyya, S., Jha, S., Tharakunnel, K., & Westland, J. C. (2011). Data mining for credit card fraud: A comparative study. Decision Support Systems, 50(3), 602–613.

Bolton, R. J., & Hand, D. J. (2002). Statistical fraud detection: A review. Statistical science, 17(3), 235-255.

Bornmann, L., Haunschild, R., & Hug, S. E. (2018). Visualizing the context of citations referencing papers published by Eugene Garfield: A new type of keyword co-occurrence analysis. Scientometrics, 114(2), 427-437.

Cressey, D. R. (1953). Other people's money; a study of the social psychology of embezzlement.

Dalla Pellegrina, L., & Masciandaro, D. (2009). The risk-based approach in the new European anti-money laundering legislation: a law and economics view. Review of law & economics, 5(2), 931-952.

Derrig, R. A. (2002). Insurance fraud. *Journal of Risk and Insurance*, 69(3), 271-287.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. American Sociological Review, 48(2), 147–160. https://doi.org/10.2307/2095101.

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of business research*, 133, 285-296.

Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv preprint. https://arxiv.org/abs/1702.08608

Ellegaard, O., & Wallin, J. A. (2015). The bibliometric analysis of scholarly production: How great is the impact?. Scientometrics, 105(3), 1809-1831.

Eling, M., & Lehmann, M. (2018). The impact of digitalization on the insurance value chain and the insurability of risks. Geneva Papers on Risk and Insurance – Issues and Practice, 43(3), 359–396. https://doi.org/10.1057/s41288-017-0073-0

Financial Action Task Force (FATF). (2004). Money laundering & terrorist financing through the insurance sector. FATF/OECD. Paris, France.

Financial Action Task Force (FATF). (2023). Guidance on anti-money laundering and counter-terrorist financing measures and financial inclusion. FATF/OECD. Paris, France.

Ferwerda, J., & Reuter, P. (2019). Learning from money laundering National Risk Assessments: the case of Italy and Switzerland. *European Journal on Criminal Policy and Research*, 25(1), 5-20.

Ghosh, S. (2020). Artificial intelligence in financial crime risk management. *Journal of Financial Crime*, 27(2), 325–335. https://doi.org/10.1108/JFC-11-2019-0140

Gilmore, W.C. (1995), Dirty Money: The Evolution of Money Laundering Counter-Measures, Council of Europe Press, Strasbourg, p. 37.

Hassan, W., & Duarte, A. E. (2024). Bibliometric analysis: a few suggestions. Current problems in cardiology, 49(8), 102640.

He, P. (2010). A typological study on money laundering. *Journal of Money Laundering Control*, 13(1), 15-32.

Hernandez Aros, L., Bustamante Molano, L. X., Gutierrez-Portela, F., Moreno Hernandez, J. J., & Rodríguez Barrero, M. S. (2024). Financial fraud detection through the application of machine learning techniques: a literature review. Humanities and Social Sciences Communications, 11(1), 1-22.

International Association of Insurance Supervisors (IAIS). (2019). Insurance Core Principles, Standards, Guidance and Assessment Methodology: ICP 22 – Anti-Money Laundering and Combating the Financing of Terrorism. IAIS. Basel, Switzerland.

Kaur, M., & Saini, M. (2024). Role of Artificial Intelligence in the crime prediction and pattern analysis studies published over the last decade: a scientometric analysis. Artificial Intelligence Review, 57(8), 202.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291. https://doi.org/10.2307/1914185.

Kane, E. J. (1981). Accelerating inflation, technological innovation, and the decreasing effectiveness of banking regulation. *The Journal of Finance*, 36(2), 355–367. https://doi.org/10.1111/j.1540-6261.1981.tb00449.x

Kuhn, T.S. (1962). The Structure of Scientific Revolutions. Chicago, IL: University of Chicago Press.

Kuzmenko, O., Šuleř, P., Lyeonov, S., Judrupa, I., & Boiko, A. (2020). Data mining and bifurcation analysis of the risk of money laundering with the involvement of financial institutions. *Journal of International Studies*, 13(3), 332-339. doi:10.14254/2071-8330.2020/13-3/22

Levi, M. (2017). Assessing the trends, scale and nature of economic cybercrimes: overview and Issues: In Cybercrimes, cybercriminals and their policing, in crime, law and social change. Crime, law and social change, 67(1), 3-20.

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In Advances in Neural Information Processing Systems (Vol. 30, pp. 4765–4774). Curran Associates, Inc. https://doi.org/10.48550/arXiv.1705.07874

Miyazaki, A. D. (2009). Perceived ethicality of insurance claim fraud: Do higher deductibles lead to lower ethical standards? *Journal of Business Ethics*, 87, 589–598. https://doi.org/10.1007/s10551-008-9960-4.

Ofoeda, I., Agbloyor, E. K., Abor, J. Y., & Osei, K. A. (2022). Anti-money laundering regulations and financial sector development. *International Journal of Finance & Economics*, 27(4), 4085-4104.

Picard, P., 1996, Auditing Claims in the Insurance Market With Fraud: The Credibility Issue, *Journal of Public Economics*, 63: 27-56.

Ramada, D. P. (2022). Prevention of Money Laundering: Various Models, Problems and Challenges. *Journal of Law and Legal Reform*, 3(1), 67-84.

Ribeiro, M. T., Singh, S., & Guestrin, S. (2016). "Why should I trust you?": Explaining the predictions of any classifier. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 1135–1144). ACM. https://doi.org/10.1145/2939672.2939778

Saha, S., Hasan, A. R., Mahmud, A., Ahmed, N., Parvin, N., & Karmakar, H. (2024). Cryptocurrency and financial crimes: A bibliometric analysis and future research agenda. Multidisciplinary Reviews, 7(8), 2024168-2024168.

Schneider, F. (2010). Turnover of organized crime and money laundering: some preliminary empirical findings. Public choice, 144(3), 473-486.

Schneider, F., & Windischbauer, U. (2008). Money laundering: some facts. *European Journal of Law and Economics*, 26(3), 387-404.

Subudhi, S., & Panigrahi, S. (2020). Use of optimized Fuzzy C-Means clustering and supervised classifiers for automobile insurance fraud detection. *Journal of King Saud University-Computer and Information Sciences*, 32(5), 568-575.

Tennyson, S. (2002). Insurance experience and consumers´ attitudes toward insurance fraud. *Journal of Insurance Regulation*, 21(2), 35–55.

Thanasegaran, H., & Shanmugam, B. (2008). Exploitation of the insurance industry for money laundering: the Malaysian perspective. *Journal of Money Laundering Control*, 11(2), 135-145.

Truman, E. M., & Reuter, P. (2004). Chasing dirty money: The fight against anti-money laundering. Peterson Institute Press: All Books.

Tseng, L. M., & Kuo, C. L. (2014). Customers' attitudes toward insurance frauds: an application of Adams' equity theory. *International Journal of Social Economics*, 41(11), 1038-1054.

Tiwari, M., Gepp, A., & Kumar, K. (2020). A review of money laundering literature: the state of research in key areas. Pacific Accounting Review, 32(2), 271-303.

Viaene, S., & Dedene, G. (2004). Insurance fraud: Issues and challenges. The Geneva Papers on Risk and Insurance-Issues and Practice, 29(2), 313-333.

Walker, J., & Unger, B. (2013). Measuring global money laundering: the 'Walker Gravity Model'. In Research handbook on money laundering (pp. 159-171). Edward Elgar Publishing.

Wang, M., Zhang, X., Yang, Y., & Wang, J. (2025). Explainable Machine Learning in Risk Management: Balancing Accuracy and Interpretability. *Journal of Financial Risk Management*, 14(3), 185-198.

Weber, T., Staake, T., & Fleisch, E. (2018). Rule-based versus machine learning-based fraud detection in the insurance sector: A comparison. Decision Support Systems, 110, 1–12. https://doi.org/10.1016/j.dss.2018.03.011

How to cite this article: Şahin, E. E., Aktan, C., Aydın, M. (2025). Mapping financial crimes in the insurance industry: A bibliometric analysis of money Laundering and fraud literature. *International Journal of Insurance and Finance, 6*(1), 69-98. https://doi.org/10.52898/ijif.2026.5