

Application of Artificial Intelligence Techniques to Combat Money Laundering in the Banking Sector

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Abstract

Money laundering is a global concern that demands attention. It poses a severe threat to financial stability and international security whereby research in anti-money laundering becomes of critical significance. Further, it is estimated that only 0.2% of money laundered through the financial system is seized. In this respect, banking institutions remain the most common avenue for money laundering, whereby multiple global banking organizations have been heavily fined for poor anti-money-laundering practices the last few years. Further, the crime itself is becoming highly sophisticated and complex, whereby the continuous amplification of its volume increases banks' vulnerability in the absence of adequate anti-money laundering specific systems. Given the significance of banking institutions in the sphere of money laundering, an emerging interest from practitioners and researchers concerning innovative solutions has been sought to alleviate challenges more effectively and improve anti-money-laundering activities. In this context, researchers have begun to explore the feasibility of artificial-intelligence techniques. However, a systematic knowledge gap was identified pertaining to a comprehensive review that rigorously analyzes and synthesizes artificial-intelligence techniques for anti-money-laundering activities in the banking sector. Therefore, this thesis aimed at filling this knowledge gap by answering the main research question: *how can the combat against money laundering in the banking sector be supported by using artificial-intelligence techniques?* This was achieved by performing a systematic literature review, whereby a documentary research was applied in the data-collection stage of conducting the literature review and the principles of grounded theory were used to perform the data analysis. The findings of this thesis indicate a number of ways by which the combat against money laundering in the banking sector can be supported through the application of various artificial-intelligence techniques spanning multiple application domains. The reviewed publications all focused on anti-money-laundering approaches which was categorized into the five main application domains *risk evaluation*, *pattern/anomaly discovery*, *case prioritization*, *visual analysis*, and *decision support*, and further into the three focus areas *prevention*, *detection*, and *investigation*. Furthermore, multiple advantages were identified and categorized under the three overarching advantageous approaches *risk-based approach*, *transaction monitoring approach*, and *holistic investigation approach* as to how the proposed techniques contribute to the different application domains and, thereby, underpin the combat against money laundering in the banking sector. Overall, they enable the banks to mitigate risk, detect suspicious activities, and holistically investigate suspicious cases in their growing role to combating money laundering. Consequently, the findings contribute to the overall knowledge base concerning the field of anti-money laundering from the perspective of the banking sector. Future research directions were further pinpointed as a result of identified limitations.

Keywords: *Money Laundering · Anti-Money Laundering · Artificial Intelligence · Banking Sector · Systematic Literature Review*

Synopsis

BACKGROUND	Striking headlines about money laundering continue to dominate various news sources. Although money laundering can take various methods and vary in both complexity and sophistication, banking institutions remain the most common channel for this. However, multiple global banking organizations have been heavily fined for poor anti-money-laundering (AML) practices in recent years. Thus, it has become evident that banks have failed with the implementation of adequate AML specific systems. Consequently, emerging interest from practitioners and researchers concerning innovative solutions has been sought to alleviate challenges and improve AML activities whereby researchers have begun to explore artificial-intelligence (AI) techniques.
PROBLEM	Money laundering is considered a global concern posing a severe threat to financial stability and international security whereby research within AML becomes of critical significance. This thesis addresses the systematic knowledge gap concerning a comprehensive review that rigorously analyzes and synthesizes AI techniques for AML activities in the banking sector.
RESEARCH QUESTION	This study aimed at filling the knowledge gap pertaining to a comprehensive evidence-based review that rigorously analyzes and synthesizes existing literature on the application of AI techniques to various approaches in the combat against money laundering in the banking sector by answering the main research question: <i>How can the combat against money laundering in the banking sector be supported by using AI techniques?</i> The main research question was further divided into sub-questions: <i>Which AI techniques and algorithms are predominantly suggested in the literature, and for which approaches to AML?</i> and <i>What are the outcomes of the AI-proposed methods?</i>
METHOD	The selected research strategy for this current thesis was systematic literature review as it is suitable for research with the purpose to obtain an objective overview concerning the evidence-based knowledge on a topic. Further, this thesis was guided by the Grounded Theory Literature Review Method for conducting a systematic and rigorous literature review. Thus, a documentary research was applied in the data-collection stage of conducting the literature review and the principles of grounded theory were used to perform the data analysis.
RESULT	A number of different techniques were identified which were applied to five main application domains within three focus areas. The advantages were categorized by the particular application domain which resulted in a total of 11 advantages within three main categories. Consequently, the results showed that using AI in the field of AML can support the combat against money laundering in the banking sector in numerous ways. The banks can adopt AI in a wide range of application domains whereby it can be leveraged to augment the different approaches to AML.
DISCUSSION	The findings of the thesis contribute to the knowledge base concerning the field of AML from the perspective of the banking sector and, thus, broadening the exploration where less focus has been placed in previous research. The thesis is interesting to practitioners by providing a knowledge base comprising an evidence-based overview of appropriate AI solutions for various application domains in AML. A limitation concerns that most studies were focused on the detection area among the publications included in the SLR indicating an unequal distribution of the overall supporting impact of AI for the remaining application domains.

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List of Abbreviations

AI	Artificial Intelligence
AICAF	Anomaly Index Computation based on Amount and Frequency
AID3	Advanced Dichotomiser 3
AI HLEG	The European Commission’s High-Level Expert Group on AI
AIRE	Anomaly Index using Rang and Entropy
AML	Anti-Money Laundering
ANN	Artificial Neural Network
ANFIS	Adaptive Neuro-Fuzzy Inference System
BLR	Bayes Logistic Regression
BIDT	Bitmap Index-based Decision Tree
BN	Bayesian Network
CBLOF	Cluster-Based Local Outlier Factor
DT	Decision Tree
EM	Expectation Maximization
FATF	The Financial Action Task Force
FI	Financial Institution
GDP	Gross Domestic Product
ID3	Iterative Dichotomiser 3
IMF	The International Monetary Fund
IF	Isolation Forest
iMST	Improved Minimum Spanning Tree
IS	Information Systems
LR	Logistic Regression
NLP	Natural Language Processing
RBF	Radial Basis Function
RF	Random Forest
RLFM	Risk Level Finding Method
RLS	Recursive Least Square
SAR	Suspicious Activity Report
SARDBN	Suspicious Activity Reporting using Dynamic Bayesian Network
SLR	Systematic Literature Review
SVM	Support Vector Machine
TEART	Transformed Euclidean Adaptive Resonance Theory
UNODC	The United Nations Office on Drugs and Crime

1 Introduction

This chapter introduces the topic by providing background information as well as presenting related work on which the research problem is based. It further outlines the definitions and scope, the research aims and questions, the research contributions as well as the overall structure of the thesis.

1.1 Background

Breaking stories and top headlines related to money laundering like “Student charged in connection with alleged €1.5m money laundering operation,” (Independent, 2020) “Dartford money launderer stashed cash in supermarket bags,” (BBC News, 2020a) “Guatemalan ex-economy minister charged with laundering drugs money,” (BBC News, 2020b) “Brazil ex-President Lula loses appeal against corruption conviction,” (BBC News, 2018a) “North Shields money launderer built social club in garden,” (BBC News, 2020c) “Two charged in money laundering investigation,” (BBC News, 2019) and “Deutsche Bank headquarters raided over money laundering” (BBC News, 2018b) continue to dominate front pages of newspapers and other news sources. According to Broek (2015), this points to continuing global efforts to combat money laundering.

Money laundering refers to the process whereby “proceeds from a criminal activity are disguised to conceal their illicit origins” (Schott, 2006, p. I-1). The process typically involves three stages: placement, layering, and integration. Placement involves introducing illegal money into the legitimate financial system. Layering involves concealing the illegitimate source of the money by carrying out a series of financial transactions. Integration involves reintroducing illegal money into the legitimate economy and into the financial system to make it appear as legitimate whereby it can be legally retrieved and used for any purpose (Cox, 2011). According to Ejanthkar & Mohanty (2011), the key drivers of money laundering include corruption, organized crime, financial fraud, drugs, and terrorist financing. Today, money laundering is recognized as the third-largest industry in the world constituting a major threat to the stability of financial institutions (FIs) as well as society at large (Le-Khac et al., 2009).

The scale of money going through the laundering cycle is rather difficult to assess. However, the International Monetary Fund (IMF) estimated that the annual aggregated size of money laundering transactions is somewhere between two to five percent of global gross domestic product (GDP) (UNODC, 2011), or \$2.8 trillion and \$7.1 trillion according to statistics for 2019 (BAE Systems, 2020). Nevertheless, the United Nations Office on Drugs and Crime (UNODC) states that less than one percent of these funds are seized (UNODC, 2011). Thus, current efforts aimed at preventing money laundering are failing (Arslanian & Fischer, 2019) whereby anti-money-laundering (AML) research is “of critical significance to national financial stability and international security” (Gao & Ye, 2007, p. 170).

The global development of AML is considered an important response to the threat posed by money laundering (Tai & Kan, 2019). Although the rise in laws and regulations against money laundering can add to difficulty for launderers, it does not provide an effective solution for detecting the act (Tai & Kan, 2019). AML systems have been implemented by FIs worldwide in the ongoing efforts to combat money laundering. Nevertheless, FIs worldwide have also been issued with fines of more than \$27 billion since the recent financial crisis due to breaches of AML sanctions (Fenergo, 2018). In addition, the Basel Institute on Governance recently published its annual Basel AML Index map whereby the country risk of money laundering worldwide is assessed and ranked accordingly (ICAR, 2020). The risk scores are based on data from sources such as the Financial Action Task Force (FATF), Transparency International,

the World Bank, and The World Economic Forum. It was emphasized that average risk scores are too high whereas the ranking performance has worsened in 35 countries compared to the previous year. Further, recent money-laundering scandals that received substantial media attention engulfed banks in the Nordic countries, which are low-risk countries according to the Basel AML Index map. Nevertheless, it was stated that “too many countries’ financial systems remain too exposed to money laundering” (Basel Institute on Governance, 2020, para. 4). It has been acknowledged that the trend of poor rates has been evident since the FATF started conducting a fourth-round evaluation methodology where the effectiveness of AML systems is assessed beside the technical compliance. Consequently, countries have been rated poorly concerning the effectiveness of the systems in practice. Therefore, it was stated in Basel Institute on Governance (2020, para. 11) that “A lot of countries may have strong systems in place, but in practice they are not working.”

Moreover, approaches to AML can be rule based or risk based, where the latter require FIs to identify and assess the money-laundering risk they are exposed to and prioritize their AML activities accordingly (FATF, 2014). Nevertheless, most banks “rely on rule-based systems to filter out any suspicious transactions based on pre-generated static rules” (Chen et al., 2018, p. 246). These systems flag suspicious transactions according to the pre-defined fixed rules and thresholds requiring intensive resource utilization to review these flagged transactions to sort out the false positives. Considering that the rules are set in advance, launderers can bypass them by adapting their techniques to comply with the rules while the rules can also generate an unmanageable number of flagged transactions due to many of them being falsely flagged (Hossam et al., 2016). Further, the ongoing digitalization enabling new payment systems has transformed the transaction activity due to the ease of use and speed of online transactions (Tropina, 2014). Thus, conventional approaches rather consume “a large amount of manual efforts from anti-money laundering specialists, who require long-time training” (Tai & Kan, 2019, p. 379). Hence, current AML systems are rather inefficient at identifying money-laundering activity resulting in increased manual, repetitive, and data-intensive tasks (Craig, 2019; Han et al., 2018).

Finally, although money laundering can take various methods and vary in both complexity and sophistication, banking institutions remain the most common channel for money laundering (Demetis, 2018; Unger, 2017). Regardless of current efforts, Han et al. (2018) emphasize that multiple global banking organizations have been heavily fined for poor AML practices the last few years (see e.g., Huang, 2015; Mullen, 2017; Shane, 2018). Thus, it has become evident that banks have failed with the implementation of adequate AML-specific systems (Demetis, 2018). This, together with ever-evolving regulations, has emphasized the necessity for better technology to support AML activities (Singh & Best, 2019). In addition, it was found in research conducted by BAE Systems (2020) that almost half (43%) of banks and insurers in the study report they want to invest in better and more effective technology as part of their AML investment strategies for the next five years. Furthermore, Kurum (2020) conducted Delphi surveys where the opinion of experts was studied regarding the future trends in the use of technology for tackling money laundering. The researcher found that experts deemed artificial intelligence (AI) likely to be the main impactful technology for FIs in this context. Consequently, an emerging interest from practitioners and researchers concerning innovative solutions has been sought to alleviate challenges more effectively and improve AML activities (Arslanian & Fischer, 2019; Singh & Best, 2019) whereby researchers have begun to explore the feasibility of AI techniques (Chen et al., 2018). However, although the important role of technology has been acknowledged in the fight against money laundering, this “socially important phenomenon has been examined sparingly in Information Systems (IS) research” (Demetis, 2018, p. 96).

1.2 Research Problem

Money laundering is considered a global concern that demands attention (Hendriyette & Grewal, 2017; Perryer, 2019). In addition to the risks it poses for FIs such as reputation, operational, and legal risk, it could at the society level facilitate the expansion of criminal activities (Gjoni et al., 2015; Le-Khac et al., 2009). It has also been found that increases in money-laundering activities have an adverse impact on annual economic growth rates (Gjoni et al., 2015; UNODC, 2011). Moreover, money laundering is becoming increasingly sophisticated (Le-Khac et al., 2009), while at the same time, regulatory requirements are becoming increasingly demanding and the increase of data continuous (Kurum, 2020). In line with this, only 0.2% of money laundered through the financial system is estimated to be seized (UNODC, 2011). This poses a severe threat to financial stability and international security whereby research within AML becomes of critical significance (Gao & Ye, 2007; Le-Khac et al., 2010; Le-Khac et al., 2009).

Given its importance, it is no surprise that the literature on AML is fast growing. In recent years, various studies have been published on AML whereby technological developments have been acknowledged to bring a broad range of opportunities. The background section describes the shortcomings and ineffectiveness of the contemporary approaches to AML, whereas the selection of related work in the subsequent chapter emphasizes the continued challenge while indicating the call for additional concentrated and systematic research expanding the scope of current ones to be performed in the context of AML. Further, previous reviews in this area focused on particular application domains of the AML approaches like the detection of suspicious activities (Chen et al., 2018), other stakeholders than banking institutions (Singh & Lin, 2020), and on subsets of technologies (Rohit & Patel, 2015; Salehi et al., 2017; Singh & Best, 2019). Thus, they have left out other types of techniques and application domains that might prove to have a valuable role in the fight against money laundering. Chen et al. (2018, p. 277) stated that “research is needed to examine more efficient methods for AML solutions” while highlighting that “the opportunity to explore a state-of-the-art solution is still opened.” Furthermore, Kurum (2020) emphasized the relevance of studying the impact of technologies in context of AML as well as with a focus on a specific stakeholder, while Demetis (2018) and Unger (2017) mention banks as the most common route for money launderers. Consequently, money laundering is a critical issue for banks. The lack of appropriate solutions or the appropriate use of existing solutions results in increased vulnerability and exposure to money laundering, thereby posing the aforementioned threats. Thus, it is important to understand the capabilities of different technological advancements in the fight against money laundering from the perspective of the banking sector. Considering the growing interest in the application of various AI techniques in AML approaches, there is scarce research providing a holistic view of this area. Therefore, this thesis seeks to broaden the scope of previous reviews by providing a comprehensive and evidence-based assessment of various AI techniques in the combat against money laundering in the banking sector. This is achieved by performing a systematic literature review (SLR) on available research and by taking upon the suggestion made by Leite et al. (2019) to apply the snowball technique.

The problem that this thesis addresses is, therefore, the systematic knowledge gap pertaining to a comprehensive review that rigorously analyzes and synthesizes AI techniques for AML activities in the banking sector. As there exist myriad articles published in various journals and conferences, the results of this study can assist banking personnel as well as other experts within this field to discover AI solutions for different AML activities. Furthermore, it can also assist the scientific community to discover important directions where further research is needed.

1.3 Definitions and Scope

First and foremost, the initiatives against money laundering involve several participants. However, this thesis will narrow down the research area to focus on the banking sector as it remains the main target of money laundering according to Demetis (2018) and Unger (2017).

Moreover, the thesis is delimited to study the impact of AI within this field as research on specific AI techniques and algorithms in the fight against money laundering is ever growing as well as experts deem it being the predominant technology for this field in the next ten years according to the study conducted by Kurum (2020). However, the definition of the term AI has been rather vague. Therefore, this thesis will use the definition below as set forth by the European Commission’s High-Level Expert Group on AI (AI HLEG) and Figure 1 further depicts a subset of AI techniques:

“Artificial intelligence (AI) systems are software (and possibly hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.

As a scientific discipline, AI includes several approaches and techniques, such as machine learning (of which deep learning and reinforcement learning are specific examples), machine reasoning (which includes planning, scheduling, knowledge representation and reasoning, search, and optimization), and robotics (which includes control, perception, sensors and actuators, as well as the integration of all other techniques into cyber-physical systems).” (AI HLEG, 2019, p. 6)

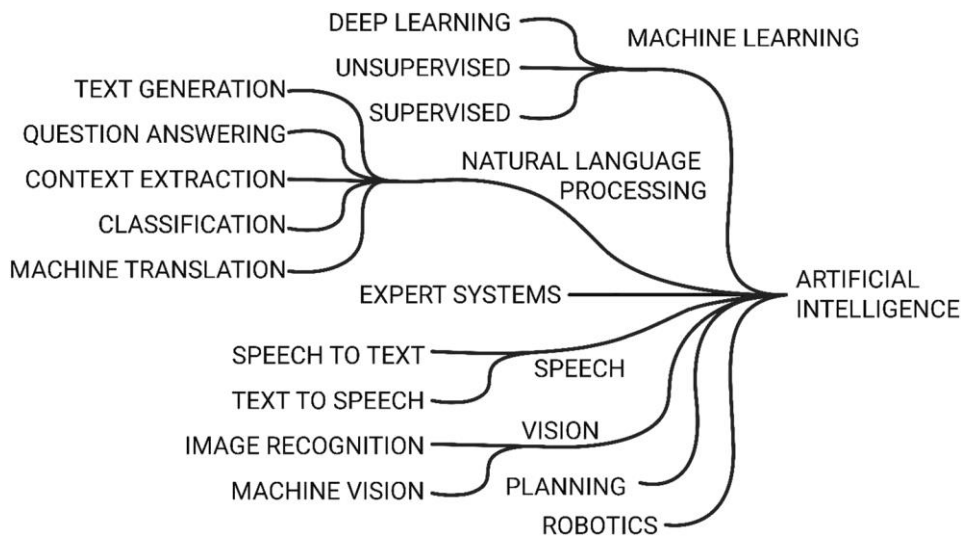


Figure 1. Components of AI (Source: Panesar, 2019, p. 76)

In addition, visualization will also be considered because with the combination “many machine learning approaches can gain better performance and interpretability” (Yu et al., 2016, p. 240) while visualization “allow the investigator to change the representation of data” and, thereby, “have substantial potential for making the detection of fraudulent transactions more efficient and effective” (Dilla & Raschke, 2015, p. 1).

1.4 Aim and Research Question

This study is aimed at filling the systematic knowledge gap pertaining to a comprehensive evidence-based review that rigorously analyzes and synthesizes existing literature on the application of AI techniques on various approaches in the combat against money laundering in the banking sector. Therefore, the main research question in this thesis is formulated as follows: *how can the combat against money laundering in the banking sector be supported by using AI techniques?* To answer the main research question, it has been further divided into sub-questions:

SQ1: Which AI techniques and algorithms are predominantly suggested in the literature, and for which approaches to AML?

- This sub-question aims to identify different AI techniques used and/or suggested, as well as to identify the AML activities for which these are applied in the literature.

SQ2: What are the outcomes of the AI-proposed methods?

- This sub-question aims to learn how the proposed techniques were evaluated, as well as to identify the advantages of the proposed techniques and, thus, the extent to which they can make AML efforts more effective.

1.5 Research Contributions

This thesis aims at making both theoretical as well as practical contributions using SLR as a method. First, Denscombe (2014, p. 132) claims that SLRs “are used by a range of social researchers, practitioners and policy-makers who want to get a reliable and objective overview of the evidence that is currently available on a specific topic or the impact of a new intervention.” Thus, the theoretical contribution of the current thesis could be that the findings can help address important directions for research according to the identified needs while simultaneously providing banking personnel and/or other experts with a reliable knowledge base in the form of a comprehensive and evidence-based overview of relevant AI techniques in the realm of AML.

Second, Denscombe (2014, p. 143) states that SLRs “produce answers that are of direct value to policy-makers and practitioners who need some guidance about ‘the truth of the matter’ in the midst of large amounts of scientific evidence.” Thus, the practical contribution of the current thesis could be that it provides practical guidance by addressing issues that banking personnel and/or other experts may encounter in terms of selecting appropriate technology in the fight against money laundering.

1.6 Thesis Structure

The rest of this thesis is structured as follows: Chapter 2 presents the scientific base; Chapter 3 presents the research strategy and methods used in this thesis; Chapter 4 presents an overview of the selected studies as well as the results; Chapter 5 provides a discussion of the obtained results, concludes the thesis as well as provides suggestions for future research directions.

2 Scientific Base

This chapter presents the scientific base of the thesis. It aims at showing how the thesis builds on existing knowledge. Thus, placing the thesis and its contribution in the context of existing research. Further, the research in this thesis provides to IS research by contributing to the area of data science, which belongs to the multidisciplinary field of computer and systems sciences. The thesis reviews AI techniques for AML thereby contributing to the discipline of data science.

Numerous efforts have previously been made to find solutions in the fight against financial fraud (i.e., credit card fraud, corporate fraud, insurance fraud, money laundering, etc.), whereby references like Albashrawi (2016), Ngai et al. (2010), Ryman-Tubb et al. (2018), and Sinayobye et al. (2018) conducted reviews in this area. Ngai et al. (2010) studied data-mining techniques to detect financial crime across different applications where they acknowledged the lack of research pertaining to money laundering. Albashrawi (2016) also studied data-mining techniques across different financial applications. The researcher classified the different fraud types wherein the corresponding data-mining techniques was presented – out of 41 techniques found in the literature, only two were identified for money laundering, thereby making it an area in need of more attention (Albashrawi, 2016). Ryman-Tubb et al. (2018) performed a survey on the use of AI and machine learning for detecting financial fraud with a focus on payment-card fraud. Sinayobye et al. (2018) also performed a review but focused on machine-learning techniques for fraud detection and identified techniques used in the following application domains: credit-card frauds, telecommunication fraud, healthcare insurance, automobile insurance, online auction frauds, and smart-meter data fraud. While these studies focus on various financial frauds, they also indicate the limited focus on money laundering.

There exists a significant body of literature on financial fraud as well as technological advancements to detect it. Although the focus has been on other types of financial crime than that of money laundering, the latter has been acknowledged as a particular type of financial fraud. However, Demetis (2018, p. 97) calls for it to be “treated as a stand-alone phenomenon.” Although the application of traditional approaches is discussed in the background, they rather generate a large number of false positives. This means that many legal transactions are marked suspicious resulting in conventional AML solutions’ being largely resource-consuming and inefficient (Han et al, 2018; Tai & Kan, 2019; Craig, 2019). Thus, effective technological solutions become important in the fight against money laundering (Singh & Best, 2019). Further, the growing threat of money laundering has attracted attention from practitioners and researchers whereby the literature on this phenomenon is expanding. Over the years, technological solutions have received recognition in the fight against money laundering and consequently gained prominence in the literature. Researchers have begun the exploration of AI techniques for approaches to AML (Chen et al., 2018) whereby references like Al-Suwaidi & Nobanee (2020), Chen et al. (2018), Leite et al. (2019), Rohit & Patel (2015), Salehi et al. (2017), and Singh & Lin (2020) conducted reviews in this area.

Chen et al. (2018) conducted a review of various machine-learning techniques for AML solutions in the detection of suspicious transactions whereby the researchers identified and analyzed solutions of AML typologies, link analysis, behavioral modeling, risk scoring, anomaly detection, and geographic capability. However, the researchers emphasize that “research is needed to examine more efficient methods for AML solutions” and highlight that “the opportunity to explore a state-of-the-art solution is still opened” (Chen et al., 2018, p. 277). In their review, a subset of AI is studied. This current thesis

provides a comprehensive review of AI techniques within this field. Furthermore, Chen et al. (2018) identified the need to examine additional methods for AML solutions. Consequently, this thesis contributes to this need by broadening the scope of their review. Rohit & Patel (2015) as well as Salehi et al. (2017) provided reviews on data-mining techniques for detecting money laundering. These reviews focus on data-mining techniques rather than providing an overarching view of different AI techniques. Further, Al-Suwaidi & Nobanee (2020) performed a review of existing work on AML and identified the need for more focused studies to be performed on detecting schemes using machine learning. While machine learning is a subset of AI and detection is an application domain of the AML approaches, it will be included in this thesis. In addition, the aforementioned studies (Chen et al., 2018; Rohit & Patel, 2015; Salehi et al., 2017; Al-Suwaidi & Nobanee, 2020) focus on detecting suspicious activities rather than including all existing application domains of the AML approaches. In this case, they have left out how different AML activities are supported by technology. Unlike these studies on the detection of money laundering, this thesis is not limited to a particular AML activity but rather includes all application domains of the AML approaches suggested in the literature thereby broadening the scope of previous reviews.

Singh & Lin (2020) explored solutions that AI and other technologies can provide for AML initiatives in charitable fundraising. Although the researchers explored AI solutions, they did so from the perspective of charitable fundraising initiatives. This thesis is, thereby, different from their research by studying the perspective of banking institutions, which is the most common method for money laundering (Demetis, 2018; Unger, 2017).

Leite et al. (2019) conducted a review of technological solutions in the fight against money laundering, whereby the researchers identified five general categories of application domains of the AML approaches where information technology is adopted and where data mining was the most commonly applied mechanism. However, the researchers state that their study cannot be regarded as exhaustive and suggest expanding the scope of their review by “including manual searches through snowball techniques in the references” (Leite et al., 2019, p. 18). This was the only review found within this context not limited to a particular AML activity. The current thesis adopts the suggestion expanding the scope of the review by including snowballing techniques as discussed in the methodology chapter.

In summary, the selection of related work emphasizes the continued challenge to eradicate money laundering while pointing towards the pivotal role of technology in this fight. Accordingly, the aforementioned literature reviews indicate the call for additional concentrated and systematic research expanding the scope of current ones to be performed in the context of AML. Consequently, this thesis builds on previous research to explore AI solutions in the sphere of combating money laundering. While previous research predominantly focused on subsets of technologies to a particular AML activity and/or from the perspective of particular stakeholders (thereby only partially covering studies on AI for AML), this thesis broadens the scope of previous reviews by focusing on providing a comprehensive and evidence-based assessment of various AI techniques in the combat against money laundering in the banking sector. Hence, this thesis broadens the exploration where less focus has been placed in earlier reviews.

3 Methodology

This chapter presents the selected methodological approach whereby the research strategy and method will be discussed and motivated. Further discussion will be provided regarding alternative methods that could be used. Thereafter, the application of the selected research strategy and method will be described followed by a description of the data analysis. Lastly, relevant ethical considerations are discussed.

3.1 Choice of Research Method

This thesis explores existing literature on the application of AI techniques on various approaches in the fight against money laundering in the banking sector. The research question guiding the current thesis is “*how can the combat against money laundering in the banking sector be supported by using AI techniques?*” whereby two sub-questions were formulated that investigates the AI techniques and algorithms that are predominantly suggested for different approaches to AML as well as the outcomes of these in the literature in order to answer the main research question.

Denscombe (2014, p. 3) emphasizes that “there is no single pathway to good research: there are always options and alternatives.” One reason is that no research strategy can be regarded good or bad nor right or wrong in itself, but it rather depends on how it is used. Therefore, the researcher should consider *suitability, feasibility, and ethics* when choosing the research strategy. He further claims that the choice of a research strategy is one of the biggest decisions a researcher needs to make (Denscombe, 2014). The selected research strategy for this current thesis is systematic literature review (SLR or systematic review) to answer the sub-questions and ultimately the main research question. As previously mentioned, Leite et al. (2019, p. 17) performed an SLR in their study with the aim to “provide evidence-based knowledge of the current state of combat money laundering through the use of information technology and areas of potential research.” Chen et al. (2018, p. 245) performed a review of the literature with the aim to “provide a comprehensive survey of machine learning algorithms and methods applied to detect suspicious transactions.” Considering that the current thesis was motivated by the identified need to broaden the scope of previous reviews, the author wants to obtain a comprehensive overview of available evidence on AI techniques to combat money laundering in the banking sector and address directions for future research. According to Denscombe (2014), SLR is suitable for research with the purpose to obtain an objective overview concerning the evidence-based knowledge on a topic. It is, therefore, considered a means of “identifying, evaluating and interpreting all available research relevant to a particular research question, or topic area, or phenomenon of interest” (Kitchenham & Charters, 2007, p. 3). Consequently, systematic reviews are defined as “a review of the research literature whose aim is to arrive at a conclusion about the state of knowledge on a topic based on a rigorous and unbiased overview of all the research that has been undertaken on that topic” (Denscombe, 2014, p.132). In addition, Kitchenham & Charters (2007) list a number of reasons for performing SLRs such as 1) summarizing existing evidence of a technology, and 2) identifying gaps in current research to direct areas for future research. Accordingly, by performing an SLR, the appropriate type of data will be produced to fulfil the aim of this thesis. Consequently, a systematic review was deemed appropriate as the research strategy for this thesis taking the two factors *suitability* and *feasibility* into consideration while also relating to previous studies with comparable characteristics of research.

Moreover, Webster & Watson (2002) emphasized the lack of review articles in the IS field, thereby encouraging more systematic reviews to be performed in this field due to its importance to strengthen it as a field of study. In addition, Demetis (2018) acknowledged the need for more money-laundering studies to be performed in IS research. This also motivated the choice of research strategy as the thesis intends to contribute to the IS field performing an SLR that could further accelerate the progress of money-laundering studies in the IS literature.

Further, this thesis will be guided by the Grounded Theory Literature Review Method as presented in Wolfswinkel et al. (2013) for conducting a systematic and rigorous literature review. Their framework constitutes a five-stage approach for this aim wherein the first three stages concern the data collection, the fourth stage concerns data analysis, and the fifth stage concerns the presentation of findings (Wolfswinkel et al., 2013).

The three stages forming the method for data collection are the search strategy, the search, and the selection. In the first stage, the appropriate dataset is defined by defining inclusion and exclusion criteria as well as choosing relevant data sources and search terms. In the second stage, the previously defined strategy is applied performing the actual search for relevant studies. In the third stage, the sample of studies to be reviewed is filtered and refined, as well as forward and backward citations checked (Wolfswinkel et al., 2013). The latter is a snowballing method that Leite et al. (2019) suggested for future research and that this thesis will employ. Snowballing refers to “using the reference list of a paper or the citations to the paper to identify additional papers” (Wohlin, 2014, p. 1). Wohlin (2014) further states that this approach is known as backward and forward snowballing. Thus, using the snowballing technique can also minimize any risk to miss valuable literature as this could bias perspectives.

Thus, documentary research is applied in the data-collection stage of conducting the literature review that will answer the research question. Documentary research is a research method using, for instance, journal articles and other publications as its source of data and that are later analyzed for the present study (Denscombe, 2014). The advantages of documentary research include its accessibility to data and cost effectiveness, whereas the disadvantages of documentary research concern the credibility of the source and the fact that using documents as the data source also implies that these data probably have been produced for other purposes than the aims of the systematic review itself (Denscombe, 2014). Therefore, the search strategy will include criteria aimed at ensuring the validity and credibility of the selection of documents.

The fourth stage consisting of the method for data analysis is where grounded theory is invoked and thereby most expressly applied. Wolfswinkel et al. (2013) suggest the data analysis to begin with selecting a random paper and during the reading process highlight anything that appear relevant to the scope of the review as well as to the research questions. This will eventually be performed on all the selected studies. Further, the researchers state that all the highlighted parts in the papers represent relevant ‘excerpts’ and, through this excerpting process, the reviewer develops a coding process that is applied systematically and wherefrom categories and concepts are derived (Wolfswinkel et al., 2013). However, this thesis will not adopt the methodological rigor of the grounded-theory approach as conceived by the originators Glaser & Strauss (1967) considering that this study does not aim at generating theories from qualitative research. Rather, it will use the key principles outlined in Wolfswinkel et al. (2013) to identify and categorize AML approaches as well as linking and classifying techniques and algorithms. These categorizations and classifications will emerge from the data, and the software program NVivo will be used for this aim.

Lastly, the reasons for choosing the framework by Wolfswinkel et al. (2013) as a guide for this thesis is mainly due to their pedagogical guidelines while simultaneously enabling more transparent and rigorous literature reviews. Another main reason is the fact that their five-stage roadmap is iterative in nature while also incorporating the snowballing approach to the search strategy. Snowballing has been acknowledged as a powerful method for conducting searches in literature studies (Badampudi et al., 2015; Greenhalgh & Peacock, 2005). Badampudi et al. (2015, p. 1) found that snowballing is comparable to database search when it comes to efficiency and that snowballing can potentially be “more reliable than a database search.” Greenhalgh & Peacock (2005, p. 1065) identify snowballing as especially powerful for “identifying high quality sources in obscure locations.”

3.2 Alternative Methods

A case study was initially considered an alternative research strategy to answer the research question in this thesis by using interviews as the main data-collection method. Case study is a research strategy focusing on a particular instance and involves in-depth investigations of that instance with the aim to “illuminate the general by looking at the particular” (Denscombe, 2014, p. 54). It, thus, enables the understanding of complex relationships and processes by allowing sufficient detailed examination of the chosen case study setting. One advantage of this research strategy is that it is well suited for small-scale research, whereas one disadvantage pertains to potential challenges in gaining access to case study settings due to ethical problems (Denscombe, 2014). Advantages of interviews involve the depth of information and the potential to gain valuable insights, whereas disadvantages of interviews involve validity of the data, reliability, and invasion of privacy (Denscombe, 2014). Although it would have been interesting to conduct a case study using interviews, potential ethical issues may be encountered concerning confidentiality and privacy issues. An example concerns disclosure of certain information that could be regarded as sensitive such as measures to AML. This could result in unwillingness to share that information with the interviewer, which could further have an adverse impact on the results in terms of the validity of the data. Furthermore, considering the aim of the study is to provide a comprehensive and evidence-based knowledge of AI techniques to combat money laundering, it would be challenging to fulfil this using these methods considering that 1) different banks may use different solutions to cope with AML challenges, and 2) many experts who provide various AML solutions are dispersed across the world. Therefore, a case study using interviews would be infeasible in terms of the workload needed to provide an exhaustive study taking a holistic view. Moreover, case studies are also inherently subjective whereby an objective overview would not be possible to obtain. This would further restrict the potential contribution of providing others guidance in terms of selection of appropriate technology for AML as it would imply that the participants in the case study must use a solution that could benefit the others. Although these issues could partly be solved by performing a survey with questionnaires in terms of the possibility to achieve wider participation, the confidentiality and privacy concerns remain. Denscombe (2014, p. 167) states that questionnaires are appropriate when, for instance, “the social climate is open enough to allow full and honest answers.” In addition, the response rates are typically rather low from those invited to participate in the survey (Denscombe, 2014). Thereby, it could result in bias and, thus, affect reliability (Denscombe, 2014). Further, considering that the participants would need relevant background within the area to be able to participate could also pose challenges to find enough participants for a questionnaire.

3.3 Application of Research Method

This section describes how the selected research strategy and methods were applied in the thesis starting with the data-collection method and subsequently the data-analysis method.

3.3.1 Data Collection

The data-collection protocol conformed to the guidelines outlined in Wolfswinkel et al. (2013) for conducting a systematic and rigorous literature review. The three stages forming the method for data collection are the search strategy, the search, and the selection, which are described further below.

Search Strategy

The search strategy is important to define to enable an efficiently performed systematic literature search, identification of appropriate field(s) of research, an optimized finding of texts in the field(s), as well as to effectively and honestly show how the search was performed (Wolfswinkel et al., 2013).

Selection Criteria

First, the search strategy involved defining the inclusion and exclusion criteria for the selection of relevant articles important for answering the sub-questions and eventually the research question. These criteria were applied in all articles in the dataset. Table 1 shows the criteria adopted for this SLR.

Table 1. Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Phenomenon	The publication addresses money laundering/anti-money laundering	The publication focuses on other financial crimes, e.g., credit fraud, etc.
Technology	The publication focuses on the use of artificial intelligence techniques	The publication focuses on other types of technologies
Stakeholder	The publication focuses on the perspective of banking sector	The publication focuses on other stakeholder perspectives
Publication	The publication has been peer-reviewed; available in full text; scientific	Publication not peer-reviewed; not available in full text; non-scientific
Language	The publication is available in the English language	The publication is not available in the English language
Other	None	Duplicate publications, other SLRs, unpublished research

Fields of Research

Second, the search strategy involved identifying the appropriate fields of research. The topic in focus in this thesis comprises money laundering and the wide area of AI. Fields of research that have been engaged with this comprise IS, data science, information management, software engineering, information technology, as well as financial crime. Other disciplines have also engaged with money laundering; however, the focus is on exploring AI techniques in the fight against money laundering whereby disciplines engaged with money laundering focusing on, for instance, financial and economic implications of money laundering, legislation, management, and actor perspective is not included as the review is limited to those containing the most relevant texts for answering the research question. Further, the review was not limited to a specific timeframe in order to enable a broader scope.

Data Sources

Third, the search strategy involved selecting appropriate data sources for finding the most relevant texts for answering the research question. The data sources in this review comprised two electronic databases (Table 2). Google Scholar was deliberately excluded as a data source in this review due to the overlap with the selected databases. These were chosen because they cover the aforementioned relevant fields of research, thereby ensuring the coverage of relevant publications from relevant journals and conferences. Another reason pertains to the ease of access to these electronic databases through the Stockholm University Library. Furthermore, backward and forward citations were checked on applicable publications to complement the database search to ensure the inclusion of relevant publications was maximized and, thus, to ensure a comprehensive review.

Table 2 below provides a quick overview of the data sources for the search included in this review, the search field used wherein the actual search is performed to retrieve relevant publications, and the number of publications found from each data source. The reason concerning the differences in the search fields pertains to the search functionalities of the electronic databases. Furthermore, only peer-reviewed publications were considered as well as the English language was pre-selected when performing the advanced search.

Moreover, additional details are provided in Appendix A. In this case, a detailed overview concerning backward and forward snowballing from each electronic database with the specific publications retrieved from backward and forward snowballing is provided. In addition, details concerning specific publications retrieved from each electronic database is also provided. Thereby, emphasizing transparency as well as easy reproduction of the results.

Table 2. Data Sources: Overview

Data Source	Search Field	Publications Found
Elsevier Scopus	Title, abstract, keywords	144
Forward Snowballing	Citation tracking	227
Backward Snowballing	Reference tracking	382
IEEE Xplore	Title, abstract, keywords	80
Forward Snowballing	Citation tracking	344
Backward Snowballing	Reference tracking	129

As seen in the table above, 144 publications were identified in the electronic database Elsevier Scopus and 80 publications were identified in the electronic database IEEE Xplore. Furthermore, backward and forward snowballing were checked on the selected publications from the databases for this review (see Appendix A for further details). Backward snowballing refers to using the reference list of the specific publication(s) included in the review to find additional publications, whereas forward snowballing refers to identifying additional publications by going through those citing the particular publication(s) included in the review. In this case, 227 and 344 publications were identified from tracking the citations of the particular publications included in the review from Elsevier Scopus and IEEE Xplore respectively. Furthermore, 382 and 129 publications were identified from going through the reference list of the particular publications included in the review from Elsevier Scopus and IEEE Xplore respectively.

Search Terms

Fourth, the search strategy involved specific formulations of possible search terms applied in the aforementioned electronic databases. It was important to formulate relevant search terms in order to be able to locate as well as to maximize the coverage of relevant publications. The search terms were developed by first extracting the key elements from the research question and the topic of the thesis. However, synonyms, alternative forms, and related terms of the search terms were considered to minimize the number of missing relevant publications. Further, a preliminary search string was then constructed by using Boolean operators “AND” to connect terms and “OR” to incorporate synonyms, alternative forms, and related terms. This also conformed to the guidelines provided by Kitchenham and Charters (2007). The constructed search string was slightly modified when necessary to conform to the syntax of the search functions provided by each electronic database. Therefore, a table comprising a detailed overview is provided in Appendix A concerning the exact search string used in each electronic database.

The following key elements were identified: money laundering, AML, AI techniques, approach, activity, banking sector. The search terms were composed of these as well as of synonyms, alternative forms, and related terms. For AI techniques, Figure 1 was used to include subsets of AI in the search string. Hence, the following preliminary search string was constructed:

(“money laundering” OR “fight money laundering” OR “fight against money laundering” OR “combat money laundering” OR “combating combat money laundering” OR “prevent money laundering” OR “money laundering prevention” OR “detect money laundering” OR “money laundering detection” OR “anti-money laundering” OR “AML”) AND (“artificial intelligence” OR “artificial intelligence techniques” OR “artificial intelligence algorithms” OR “AI” OR “AI techniques” OR “AI algorithms” OR “data science” OR “machine learning” OR “supervised” OR “unsupervised” OR “natural language processing” OR “expert systems” OR “data visualization” OR “deep learning” OR “classification” OR “robotics” OR “automation”) AND (“approach” OR “activity” OR “method” OR “framework” OR “domain” OR “process”) AND (“banking sector” OR “banking industry” OR “banking” OR “bank” OR “transaction”)

Search

The search stage involved the actual search where the search strategy above was applied. The search was eventually performed across both selected electronic databases whereby backward and forward citations were checked on applicable publications generated by each database. It was also during this stage of performing the actual search that the search strategy was revisited and iteratively refined when necessary. For instance, if a search term turned out to yield a considerable number of irrelevant results, then it would become appropriate to revisit and refine the search terms to eliminate irrelevant results. Likewise, if it became apparent that some important synonym, alternative form, and/or related term of a search term was missing, then it would become relevant to revisit and refine the search terms to allow the electronic database to maximize the production of relevant results. Furthermore, all searches, search terms, sources, and their results were documented as was emphasized by Wolfswinkel et al. (2013). Thus, ensuring transparency as well as easy reproduction of the results. The documentation can be found in Appendix A.

Select

The select stage involved the actual selection of the sample of texts. It was also in this stage that backward and forward citations were applied.

First, an initial screening was performed on all articles retrieved from the electronic databases to filter out duplicates. The papers that were included represent *A articles* in Figure 2. Then, each paper was screened by reading the titles and abstracts in order to assess them against the selection criteria (Table 1). During this phase, the papers were either included to proceed to the subsequent screening phase or directly excluded due to the paper's not corresponding to the inclusion criteria. However, some papers did not fall in either of these decisions whereby a certain decision could not be made by screening only the titles and abstracts. Therefore, these papers were also included to proceed to the subsequent screening phase. The papers that were included here represent *B articles* in Figure 2. The subsequent step involved refining the sample based on reviewing the full text of each paper that was not excluded in the previous phase. All papers were assessed against the selection criteria, and those that did not correspond to the inclusion criteria were excluded. The papers that were included here represent *C articles* in Figure 2. Forward and backward citations were then checked on all included papers. The new papers that appeared during the forward and backward reference searching represent *D articles* in Figure 2. Thus, for every paper that appeared during the forward and backward reference searching, the preceding steps were carried out. This continued until saturation was reached, meaning no new relevant papers appeared. Figure 2 below illustrates the entire selection process. A more detailed view concerning the selection process applied to each electronic database is captured in Appendix A.

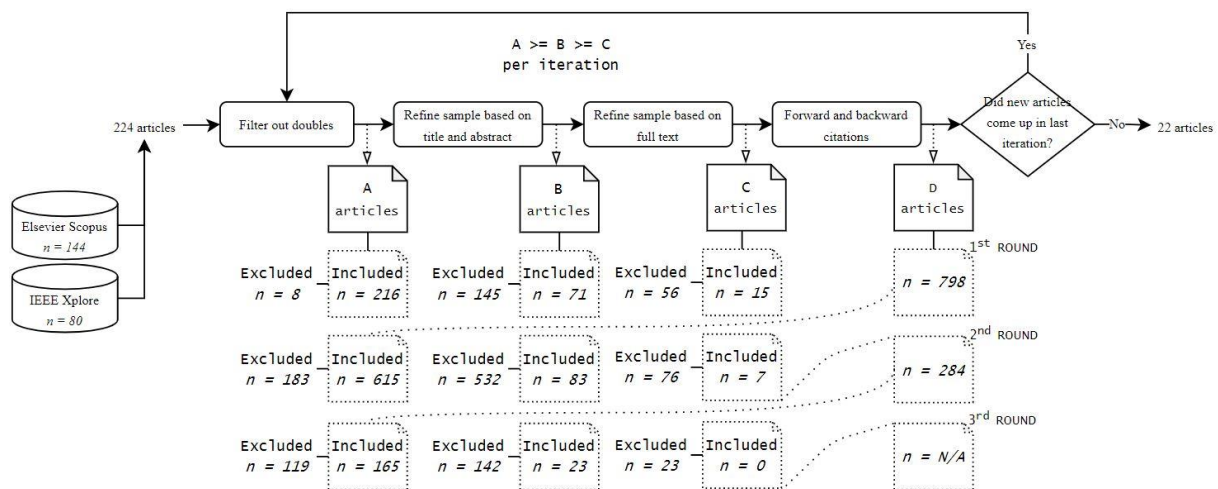


Figure 2. The Selection Process (Modified from source: Wolfswinkel et al., 2013, p. 5)

Furthermore, Wolfswinkel et al. (2013) suggested to construct a table from the dataset for structuring as well as for explicating the rationale behind the choice of papers in the selection process. Table 3 was used for this aim, and a complete table capturing all details is provided in Appendix A.

Table 3. Individual Reviewer's Selection (Source: Wolfswinkel et al., 2013, p. 5)

Year	Author(s)	Title	Journal	Reason(s) for its selection
1999	X	K	A	...
2000	Y	L	B	...
2001	Z	M	C	...

3.3.2 Data Analysis

In this thesis, the key principles of grounded theory as outlined in Wolfswinkel et al. (2013) were used to perform the data analysis. The key principles comprise *open coding*, *axial coding*, and *selective coding* (Wolfswinkel et al., 2013).

The selection of articles in the previous step resulted in unstructured stacks of papers that were uploaded in the software program NVivo prior to starting the analytical process. As suggested by Wolfswinkel et al. (2013), the analysis stage began with selecting a random paper and reading it. During the reading process, anything that appeared relevant to the scope of the review as well as to the research and sub-questions was highlighted. This process involved highlighting relevant words, sentences, or paragraphs. This was eventually performed on all the selected studies. The process of reading and highlighting was performed at least once on each paper. Furthermore, all the highlighted parts represented relevant ‘excerpts’ whereby the reviewer was involved in the aforementioned key principles, which is an ongoing coding process being applied systematically.

Open coding was applied by re-reading the excerpts wherefrom concepts and insights derived. The goal was to “identify a set of categories or a bird’s eye image of the study’s findings, with a set of theoretical and methodological insights attached” (Wolfswinkel et al., 2013, p. 6). During the reading process, codes were continuously assigned to the excerpts. However, when finishing reading one paper and moving to another, new insights could be gained. Each time this would occur, the reviewer would need to revisit earlier read papers to change an earlier identified concept and/or category. In this way, a constant ‘comparative analysis’ was applied, meaning “continuously comparing, relating and linking the identified categorizations with each other and the studied papers and excerpts” (Wolfswinkel et al., 2013, p. 7). This would continue until no new codes were revealed. Therefore, the chosen software program NVivo had an important role to log all codes and changes made during this ongoing coding process. *Axial coding* was applied by studying the concepts identified during the open coding whereby interrelations between these were identified and organized into higher-order categories and sub-categories. Thus, the reviewer was involved in the further development of categories. *Selective coding* was applied by integrating and refining those categories that were previously identified.

This analytical process involving open, axial, and selective coding was performed in an iterative manner until ‘data saturation’ was reached. Data saturation was reached when no new concepts or information arose during the analysis. The entire analysis was performed using NVivo and continuously documented using Microsoft Excel. Finally, an example of the coding process described above is depicted in Table 4.

Table 4. Coding Process Sample

<i>Excerpt</i>	<i>Grounded Theory Step</i>		
	Open Coding	Axial Coding	Selective Coding
“The core idea behind the approach is that the overall monthly transactions of a customer establish a defined pattern. This pattern closely matches among customers of similar characteristics and can be captured in the form of a probabilistic temporal model. Any deviation from this pattern is marked as suspicious” (Raza & Haider, 2011, p.988)	Pattern Recognition, Pattern Deviation, Detect Anomalies	Pattern/Anomaly Discovery	Detection

3.4 Ethical Considerations

Unlike research conducted using primary data, systematic reviews are performed using publicly accessible data and are therefore not collecting “deeply personal, sensitive or confidential information from participants” (Suri, 2020, p. 41). However, Suri (2020) emphasizes the powerful role of systematic reviews in influencing policy and practice, as well as steering further research whereby ethical considerations become critical. Thus, systematic reviews do carry important responsibilities (Wager & Wiffen, 2011).

First, considering that publicly accessible documents are used in this review, search biases must be given careful consideration (Suri, 2020). Typical forms of search biases include database, availability, language, and publication bias (Suri, 2020). To minimize this potential impact on this review, it is captured in the search strategy wherein the choice of data sources is made with careful consideration as well as inclusion and exclusion criteria is carefully defined. Further, Kitchenham & Charters (2007) emphasize that a key characteristic of SLRs pertains to the well-defined methodology that reduces the risk of bias. However, systematic reviews are not immune to this risk considering that unpublished research evidence and other types of findings not made public will not be included in this review, and this may further bias perspectives (Denscombe, 2014). While systematic reviews are not immune to the inclusion of unethical research, the aim to ensure an exhaustive review combined with the aim to avoid publication bias encourages the search among unpublished studies (Vergnes et al., 2010). Vergnes et al. (2010) claim that the risk of including unethical research is higher among unpublished studies. Although this review will not include unpublished research evidence and other types of findings not made public, backward and forward snowballing was employed to maintain exhaustiveness by complementing the database search to minimize the potential of bias perspective and to ensure a comprehensive systematic review while also carefully considering the search strategy to avoid the inclusion of unethical research. However, it is worth noting that the application of the snowballing technique resulted in hundreds of papers going through the selection process which was manually reviewed by one person which could result in the risk of errors in the compilation of publications used in the analysis. Yet, advantages of SLRs are characterized by rigorous and transparent approaches of reviewing the literature, which further strengthens the credibility of the findings, as well as by their practical value in terms of producing evidence-based answers relevant for practitioners (Denscombe, 2014). However, a disadvantage pertains to the substantial effort they require (Denscombe, 2014; Kitchenham & Charters, 2007). Moreover, potential impacts of the findings should be critically considered whereby a systematic reviewer has the responsibility to declare sources of support and funding as well as potential conflicts of interest (Suri, 2020; Wager & Wiffen, 2011). This thesis focuses on transparency wherein any potential impacts will be disclosed. In addition, Wager & Wiffen (2011) discuss the importance of avoiding plagiarism considering that particularly systematic reviews involve citations of other works. Denscombe (2014) also emphasizes the need to take care to avoid plagiarism. Thus, careful consideration is given to avoiding plagiarized material by appropriately citing other publications be they original or rephrased expressions, images, ideas, and so forth. Lastly, Denscombe (2014, p. 324) highlights the need to “act with integrity and high professional standards” at the stage of performing the data analysis to ensure honesty in the analysis as well as avoiding the risk of bias and manipulation of data. This review employs grounded theory for analyzing the data as outlined in Wolfswinkel et al. (2013) wherein the reviewer involves in a coding process to systematically categorizing excerpts. Further, care is taken to ensure transparency during the data-analysis stage.

4 Results

This chapter presents the results and analysis. It begins by discussing the characteristics concerning the selected studies. Thereafter, it will be divided into sections dealing with the questions.

4.1 Study Characteristics

The distribution of the 22 selected studies in this review per year is depicted in Figure 3. As illustrated by the graph, publication of studies accelerated in recent years with 5 publications (22.73%) in 2020 pointing towards increasing attention. Moreover, the distribution of the 22 selected studies in this review per country is depicted in Figure 4. As illustrated by the graph, the top three countries with most publication of studies are China (27.23%), Pakistan (13.64%), and India (9.09%). Furthermore, the distribution of the selected studies in this review by author(s) over the years is depicted in Figure 5 by aggregating the previous two figures into a timeline.

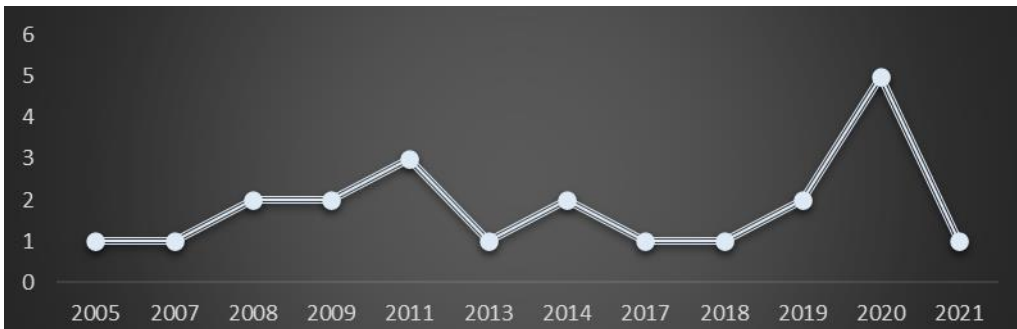


Figure 3. Distribution of Studies per Year

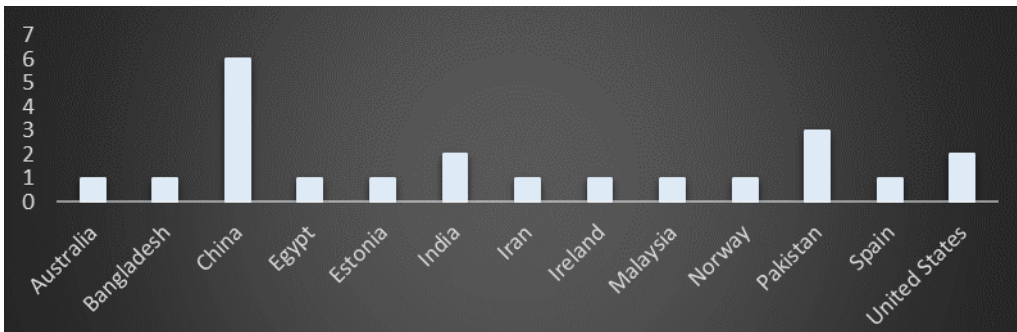


Figure 4. Distribution of Studies per Country

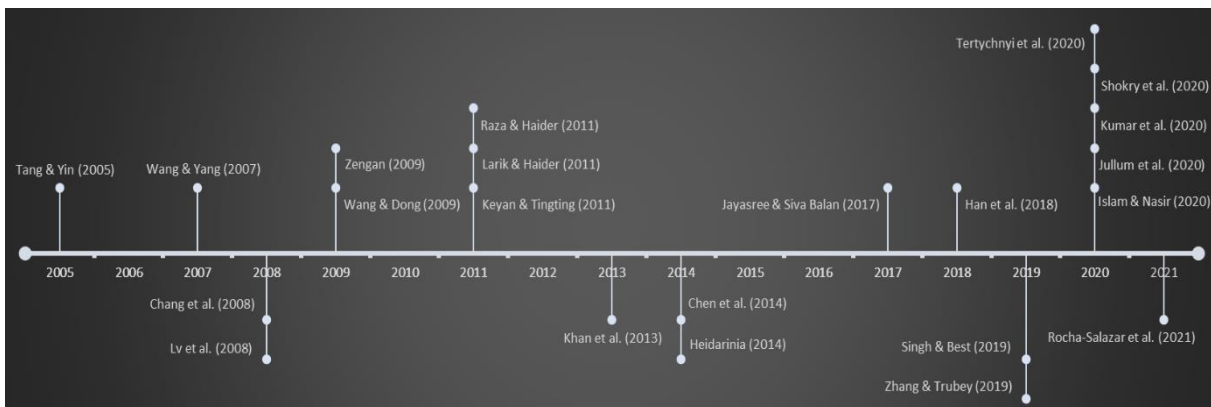


Figure 5. Distribution of Studies by Authors and Year

4.2 Techniques and Applications (SQ1)

The first sub-question in the present thesis was formulated as follows: *which AI techniques and algorithms are predominantly suggested in the literature, and for which approaches to AML?* Furthermore, this first sub-question aimed to identify different AI techniques used and/or suggested and to identify the AML activities for which these were applied in the literature.

Application Domains

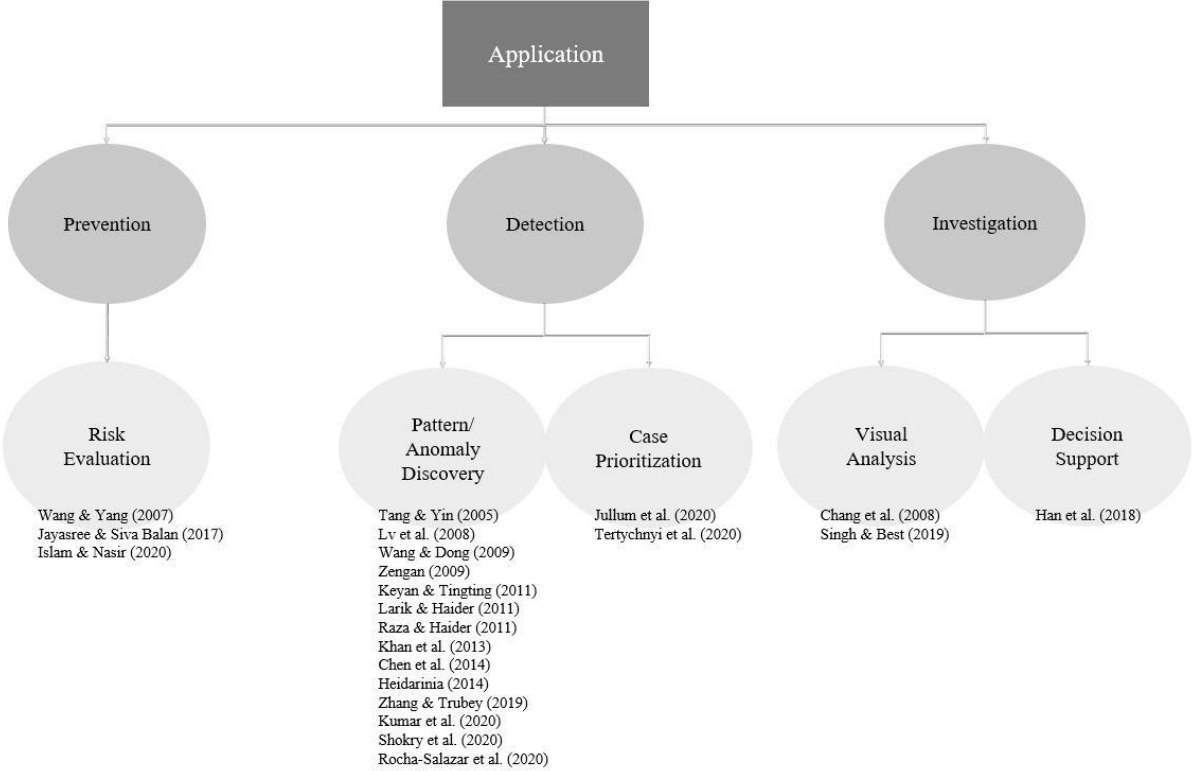


Figure 6. Identified Application Domains

This section presents the different application domains identified in the selected publications and as illustrated in Figure 6. An extended table is available in Appendix B (see Table 7). The identified application domains were further categorized under three focus areas, namely prevention, detection, and investigation. Prevention refers to the risk management and control approach. Detection refers to the proactive approach to identify money-laundering activities. Investigation refers to the investigative approach on money laundering flagged suspicions.

The application domains were categorized as risk evaluation, pattern/anomaly discovery, case prioritization, visual analysis, and decision support. Risk evaluation was categorized as an application domain under the focus area of prevention and covers approaches whose purpose is to evaluate any potential risk of money laundering by, for instance, applying risk-scoring techniques, and thereby minimize the risk level. Pattern/anomaly discovery and case prioritization were categorized as application domains under the focus area detection. Pattern/anomaly discovery covers approaches whose purpose is to detect unusual and suspicious behavior by, for instance, applying techniques that can discover activities related to money laundering. Case prioritization covers approaches whose purpose is to prioritize cases for investigation of money laundering by, for instance, applying techniques that can identify those cases worth prioritizing. Visual analysis and decision support were categorized as application domains under the focus area investigation. Visual analysis covers approaches whose

purpose is to identify relationships by, for instance, applying techniques that can enable visual analysis of patterns of activities related to money laundering. Decision support covers approaches whose purpose is to facilitate investigators by, for instance, applying techniques that can expand potential evidence of money laundering to investigators prior to decision-making.

Furthermore, Figure 6 also lists the distribution of authors focused on each application domain. The percentage distribution is further presented in Table 5 below according to the application domains and the overall focus areas. First, 13.64% (3 publications) focused on the prevention area and techniques for the risk evaluation of money laundering. Further, 72.73% (16 publications) focused on the detection area. Among these, 63.64% (14 publications) studied techniques for patterns/anomaly discovery and 9.09% (2 publications) studied techniques for case prioritization. Moreover, 13.64% (3 publications) focused on the investigation area. Among these, 9.09% (2 publications) studied techniques for visual analysis and 4.55% (1 publication) studied techniques for decision support.

Table 5. Percentage Distribution of Application Domains

% of Studies	Application Domains				
	Prevention	Detection		Investigation	
	Risk Evaluation	Patterns/Anomaly Discovery	Case Prioritization	Visual Analysis	Decision Support
%	13.64%	63.64%	9.09%	9.09%	4.55%

Thus, it becomes evident that detection has been a prominent area of focus in the research community, and, in particular, the application domain patterns/anomaly discovery. This means that previous studies have focused on techniques for identifying unusual behavior, suspicious activities, recognizing patterns and pattern deviation, as well as detecting anomalies and other similar approaches.

Figure 7 presents the distribution of publications on the three focus areas per year. While studies within the focus of prevention and investigation have appeared sporadically in time, studies within the focus of detection, however, have recurred steadily over the years from 2005 to 2021. Thereby, shedding light on the trend of investigating techniques focused on the detection area in the sphere of fighting money laundering. However, although studies within the prevention area have appeared in 2007, the figure below shows additional studies that have appeared in recent years. In the case of the investigation area, studies appear in both 2018 and 2020. Thus, this could be interpreted as an indication of new trends where the importance of prevention and investigation are realized, and where the importance of approaches seeking to prevent risks of money laundering as well as to facilitate investigations have been acknowledged in addition to the approaches seeking to detect the suspicious transactions.

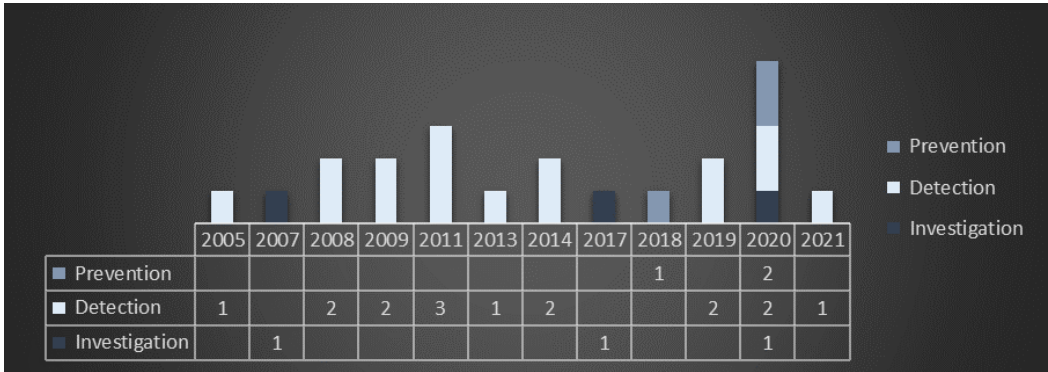


Figure 7. Distribution of Studies by Focus Areas and Year

The aforementioned application domains in Figure 6 are here combined with the corresponding techniques in Table 6 showing each technique proposed for each application domain in the selected studies. An extended table is available in Appendix B (see Table 8).

→ **Prevention – Risk Evaluation**

For example, DT (decision tree) and Naïve Bayes have been studied for approaches within risk evaluation and, thus, prevention. In Wang & Yang (2007) the authors implemented a DT method, and by generating a knowledge tree, ID3 (Iterative Dichotomiser 3) algorithm is used to evaluate the money-laundering risks posed by bank customers and, thereby, determine the risk rank and the likelihood of a particular customer to use the bank for money-laundering purposes. In addition, Jayasree & Siva Balan (2017) also proposed a DT method to evaluate the money-laundering risks, namely Bitmap Index-based Decision Tree (BIDT). The bitmap index is “a data structure which is used to effectively access larger bank databases involving money laundering accounts” whereas the DT structure is “used to partition the decision into smaller partitions for analyzing the money laundering factor” (Jayasree & Siva Balan, 2017, pp. 98-99). By generating a knowledge tree, AID3 (Advanced Dichotomiser 3) algorithm is used to analyze and determine the risk factor. Further, Islam & Nasir (2020) proposed using a method based on Naïve Bayes classification, a supervised-learning algorithm, to evaluate money-laundering risk levels of opened bank accounts and by which they call Risk Level Finding Method (RLFM). Their solution not only investigates the risk level from the time the accounts open, but also implements periodic evaluations of the bank accounts based on clients’ profile.

→ **Detection – Patterns/Anomaly Discovery**

Moreover, a number of different techniques were focused solely for approaches within patterns/anomaly detection and, thus, detection. For instance, among the selected publications, SVM (support vector machine) was studied solely for approaches within patterns/anomaly detection, specifically 28.57% (4 publications) focused on this part. For example, Tang & Yin (2005) presented a classification method for detecting unusual behavior based on SVM, which was extended to manage heterogeneous datasets by constructing an RBF (Radial Basis Function) kernel function in order to eventually replace conventional pre-defined and rule-based filtering systems. To optimize the selection of parameters of the SVM classifier, Keyan & Tingting (2011) proposed the cross-validation method for this aim. Shokry et al. (2020) implemented One Class SVM and Isolation Forest, both unsupervised-learning techniques for outlier detection, for approaches dealing with the detection of outliers and money laundering patterns. Zhang & Trubey (2018) studied five supervised-learning techniques for the detection of money-laundering activities, namely DT, RF (random forest), SVM, ANN (artificial neural network), and BLR (Bayes logistic regression). Further, Lv et al. (2008) focused on an RBF neural network model to detect suspicious activities. The model is based on APC-III clustering and recursive least square (RLS) algorithms, where the first is “used for determining the parameters of radial basis function in hidden layer” and the latter is “adopted to update weights of connections between hidden layer and output layer” (Lv et al., 2008, p. 209). Wang & Dong (2009) proposed a clustering algorithm based on iMST (improved minimum spanning tree) to detect suspicious transactions. Zengan (2009) combines distance-based unsupervised clustering and local outlier detection and, thereby, creates CBLOF (cluster-based local outlier factor) to identify unusual transactional behavioral patterns. Larik & Haider (2011) proposed TEART (transformed Euclidean adaptive resonance theory), a clustering-based approach, to identify patterns that deviate from the normal. In addition, the authors propose AICAF (Anomaly Index Computation based on Amount and Frequency) to rank transactions as

suspicious. Raza & Haider (2011) proposed a combination of clustering and dynamic BN (Bayesian network), by which they call Suspicious Activity Reporting using Dynamic Bayesian Network (SARDBN), to detect anomalies. Dynamic BN is used to “capture patterns in a customer’s monthly transactional sequences as well as to compute an anomaly index” where the AIRE (Anomaly Index using Rank and Entropy) is applied (Raza & Haider, 2011, p. 987). Khan et al. (2013) presented a BN-based approach to analyze clients’ transactional behavior to identify suspicious patterns that deviate from the clients’ normal behavior according to the defined rules. Chen et al. (2014) proposed EM (expectation maximization), a clustering-based approach, for detecting suspicious transactions. Heidarinia et al. (2014) proposed a method based on ANFIS (adaptive neuro-fuzzy inference system) that combines ANNs and fuzzy logic to detect suspicious money laundering accounts. Kumar et al. (2020) used Naïve Bayes classifier to classify transactions as illicit or non-illicit and, thereby, identify suspicious behavior related to money laundering. Rocha-Salazar (2021) proposed a model comprising three phases, where the first phase is based on fuzzy logic to define risk metrics, the second phase is based on unsupervised neural network algorithms (strict competitive learning, self-organizing map, C-means and neural gas) for clustering, and the third phase is based on an abnormality indicator in order to detect abnormal behavior.

→ **Detection – Case Prioritization**

Furthermore, DT, LR (logistic regression), and gradient boosting have been studied for approaches within case prioritization and, thus, detection. For example, Jullum et al. (2020) proposed a supervised-learning machine-learning model using gradient boosting with tree models for prioritizing those suspicious transactions that should be further manually investigated by AML investigators. Their model is built on the transactions rather than on the accounts and is trained by using “‘normal’ legal transactions; those flagged as suspicious by the bank’s internal alert system; and potential money laundering cases reported to the authorities” as well as to “predict the probability that a new transaction should be reported, using information such as background information about the sender/receiver, their earlier behaviour and their transaction history” (Jullum et al., 2020, p. 173). Tertychnyi et al. (2020) proposed a two-layered model, where the first layer is based on LR classification which filters out those clients not considered illegal, and the second layer is based on a gradient boosting model to classify those clients that remained after the filtering process from the previous layer into potentially illicit and non-illicit.

→ **Investigation – Visual Analysis**

Additionally, visualization techniques have been proposed for approaches within visual analysis and, thus, investigation. For example, Chang et al. (2008) proposed visualization techniques to assist AML investigators/analysts in monitoring transactions. They call their solution WireVis which uses the following visual analytics tools: keyword network view, heatmap, search-by-example tool, and Strings and Beads. According to the authors, these together “fully depict the relationships among accounts, time, and keywords within the transactions, and present the user with a global overview of the data, providing the ability to aggregate and organize groups of transactions for better investigation and analysis and the ability to drill-down into and compare individual records” (Chang et al., 2018, p. 64). Visualization techniques were also proposed by Singh & Best (2019) in terms of using link analysis to assist AML investigators/analysts in identifying suspicious money laundering-related patterns. The authors developed a prototype by which they call AML²ink.

→ **Investigation – Decision Support**

Lastly, NLP (natural language processing) has been proposed for approaches within decision support, and, thus, investigation. Han et al. (2018) proposed deep-learning-based NLP technologies to improve AML monitoring and provide AML investigators/analysts with additional evidence prior to final decision-making. The framework proposed by the authors performs “news and tweet sentiment analysis, entity recognition, relation extraction, entity linking and link analysis on different data sources” (Han et al., 2018, p. 37).

Table 6. Technique Distribution by Application Domains

AI Techniques	Application Domains					
	Prevention	Detection			Investigation	
	<i>Supervised Learning</i>	<i>Supervised Learning</i>	<i>Supervised Learning</i>	<i>Unsupervised Learning</i>	Visualization	<i>Deep Learning</i>
	Risk Evaluation	Case Prioritization	Patterns/Anomaly Discovery	Patterns/Anomaly Discovery	Visual Analysis	Decision Support
SVM			✓✓✓			
One Class SVM				✓		
DT	✓✓		✓			
Visualization					✓✓	
Network Analysis					✓	
Heatmap					✓	
Neural Network			✓	✓		
iMST				✓		
CBLOF				✓		
TEART				✓		
BN			✓			
Dynamic BN				✓		
EM				✓		
ANFIS						
NLP						✓
Link Analysis					✓	✓
RF			✓			
LR		✓				
BLR			✓			
ANN			✓✓			
Fuzzy Logic			✓	✓		
Naïve Bayes	✓		✓			
Gradient Boosting		✓✓				
IF				✓		

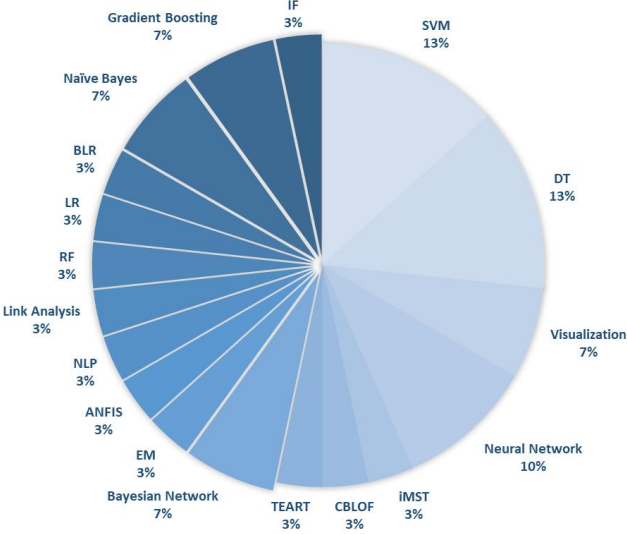
The papers distinguished between classification and clustering techniques, whereby most literature on AI for AML could be grouped into the learning types supervised and unsupervised learning. Supervised-learning techniques was applied for risk evaluation, case prioritization, and patterns/anomaly discovery, while unsupervised-learning techniques was also applied for the latter.

Within supervised-learning techniques, DT, gradient boosting, ANN, and SVM were the most common approaches in addition to BN, neural network, RF, BLR, Naïve Bayes, LR, and fuzzy logic. Within unsupervised-learning techniques, one-class SVM, neural network, iMST, CBLOF, TEART, dynamic BN, EM, fuzzy logic, and IF were presented. It was emphasized here that classification techniques “require knowledge of classes prior to their application – a requirement not easy to satisfy in many money laundering situations,” while clustering-based techniques “group customers that perform similar kind of transactions into a single cluster and then categorize either small-size clusters or outliers as anomalous” (Larik & Haider, 2011, p. 606). Thus, while Rocha-Salazar et al. (2021, p. 2) stated that “the number of verified [money laundering] cases is small compared to the number of non-verified cases,” Khan et al. (2013) emphasized that supervised-learning techniques require labelled data, which are rather difficult to obtain due to their rare availability. Therefore, Rocha-Salazar et al. (2021, p. 2) claimed the unsupervised techniques as more suitable in this context owing to the lack of ‘ground-truth data.’ However, Larik & Haider (2011) stated that unsupervised techniques might become a challenge in terms of estimating their accuracy. Although Jullum et al. (2020, p. 174) also acknowledged the problematic aspect of available data with known labels since FIs seldom learn whether a suspect of money laundering was convicted guilty or not, the authors still focused on supervised-learning techniques by arguing that “‘suspicious behaviour’ is actually what most financial institutions are indeed interested in.” Then again, Shokry et al. (2020, p. 96) concluded by stating that unsupervised learning is more suitable in this context due to “its ability to detect similarities, hidden patterns, structures or grouping across all transactions without prior training, it detects suspicious activities without knowing what suspicious activity behaviour or pattern looks like” stating that it differentiates it from supervised learning which “requires knowledge of suspicious patterns/activities to detect similar ones.”

On the other hand, Singh & Best (2016, p. 2) emphasized the role of visual representations in identifying patterns in the data wherein visualization techniques enable users “to ‘see’ information in order to help them better understand and contextualize it.” Chang et al. (2008) means that depicting the relationships among different data enable investigators to compare it and, thus, identify those aforementioned ‘suspicious behaviour’ as mentioned in Jullum et al. (2020). Finally, Han et al. (2018) means that applying deep-learning-driven NLP techniques by utilizing various types of data sources enable the collection of additional, and valuable, evidence for decisions to be made by investigators.

Figure 8 depicts a general percentage distribution of the included techniques, whereby we can see that SVM (13%), DT (13%), and neural network (10%) make the three methods studied by most authors.

Figure 8. Percentage Distribution of Techniques



4.3 Outcome of Proposed Methods (SQ2)

The second sub-question in the present thesis was formulated as follows: *what are the outcomes of the AI-proposed methods?* Furthermore, this second sub-question aimed to learn how the proposed techniques were evaluated, as well as to identify the advantages of the proposed techniques and, thus, the extent to which they can make AML efforts more effective.

Dataset and Evaluation Measures

In this section, the evaluation methods as well as the data sources for performing evaluation of the proposed techniques as outlined in Table 6 and in Appendix B (see Table 8) are described. The data sources and the evaluation methods are further captured in Appendix B (see Table 9) and a glossary is provided in Appendix C.

→ **Prevention – Risk Evaluation**

In the study performed by Wang & Yang (2007), a sample size comprising 28 randomly selected customers obtained from a data warehouse including 160 thousand customers was used with 4 selected attributes related to money laundering, namely industry, business size, location and type of bank products and services used. Further, 21 of these were used as training sample to later test the validity of this on the remaining 7 customers. The authors demonstrated the effectiveness of their methods to be used for determining the risk rank of clients. Jayasree & Siva Balan (2017) used data from Statlog German Credit Data, whereby the authors performed their experiment evaluating adaptability rate (AR), true positive rate (TPR), false positive rate (FPR), and risk identification time (RIT). The result showed that BIDT outperformed in RIT, AR, FPR, and TPR when compared to the existing methods Smart Card-based Security Framework (SCSF) and Multi-layered Detection System (MDS). Islam & Nasir (2020) used synthetic data, whereby the authors performed their experiment evaluating accuracy, TPR, FPR, precision, recall, and f-measure. The result showed that their method outperformed DT classifier by correctly classifying 93.77% of the test data and being able to classify transactions into medium risk class, which conventional methods were not able to.

→ **Detection – Patterns/Anomaly Discovery**

In Tang & Yin (2005) and Keyan & Tingting (2011), the real-world dataset included 5000 accounts and 1.2 million records spanning over seven months by which the authors simulated unusual accounts. The authors performed their experiment evaluating the accuracy, detection rate (DR) and FPR. Keyan & Tingting (2011) proposed using cross-validation method for finding the optimal parameters. In Lv et al. (2008), the real-world dataset included 6000 accounts and 1 million records spanning over eight months. The authors performed their experiment evaluating the DR and the FPR. The result showed that their method outperformed SVM and outlier detection methods. In Wang & Dong (2009), real-world dataset was gathered comprising 64 941 records with simulated unusual accounts, whereby the authors performed their experiment evaluating the number of covering clusters and proportion of anomaly points using their method. In Zengan (2009), real-world dataset in terms of 34 303 transactional data was collected from January to October 2006 while synthetic data was generated in order to test the applicability of their method. The authors performed their experiment evaluating the local outlier factor (LOF) value. In Larik & Haider (2011) and Raza & Haider (2011), a real-world dataset was used including 8.2 million transactions spanning over a year which they split into training comprising 10 months data and testing comprising two months data. Larik & Haider (2011) performed their experiment evaluating the AICAF value, whereby the result showed that their method outperformed the k-means algorithm. In Chen et al. (2014), a real-world dataset was used comprising 30 million transactions

spanning over 2 years. They performed their experiment evaluating the accuracy, whereby the result showed that their approach outperformed k-means. In Heidarinia et al. (2014), a synthetic dataset was used including 2000 customer accounts records. These were split into a training set comprising 1500 records and a test set comprising 500 records. The result showed that their solution achieved a detection accuracy of 96%. In Kumar et al. (2020), a synthetic dataset was used, whereby the authors evaluated the accuracy achieving 81.25%. In Khan et al. (2013), a real-world dataset was used comprising over 8.2 million records performed by about 100 000 customers during a year. They compared the Bayes score of the test data to the training dataset. Shokry et al. (2020) used synthetic data generated from AMLSim comprising 118 250 transactions which was evaluated by domain experts. The result showed that their method outperformed One Class SVM in time complexity and producing accurate findings. Zhang & Trubey (2018) used real-world data spanning over 13 months which they split into analysis comprising 8 months data and testing comprising 5 months data. The authors evaluated the area under the curve (AUC) and regression analysis of AUCs, and Maximum Likelihood Logistic Regression (MLLR) was used as the benchmark. Rocha-Salazar et al. (2021) used real-world data, whereby the authors performed their experiment evaluating accuracy, the error rate (ERR), and the balanced error rate (BERR). The proposed solution outperformed the previous rule-based method.

→ **Detection – Case Prioritization**

In Jullum et al. (2020), the real-world dataset comprised transactions from April 2014 to December 2016. The dataset included alert-based transactions as well as random sets of normal transactions and was collected from DNB bank. The data was split in two in order to use one set for training and the other for evaluating the model. They measured the performance using the Brier score, the AUC, and the proportion of positive predictions (PPP) where the latter was invented by the authors themselves. The result showed that their model outperformed the current rule-based system. In Tertychnyi et al. (2020), the two-layered approach was validated on a real-world dataset from approximately 330 000 customers across three countries comprising customer profiles and histories of transaction. They used Area Under the Precision-Recall Curve (AUPRC) for measuring performance and the results showed that their two-layered model outperformed a single-layer model.

→ **Investigation – Visual Analysis**

In Chang et al. (2008), the sanitized real-world dataset comprised transactions sampled over 12 months and was evaluated through a case study where the system was used by some members of the Risk Management and Compliance groups of Bank of America in order to evaluate the usefulness. Unfortunately, expert evaluators could not use the system due to specific security-related and software restrictions adversely affecting the installation of the tool within the scope of their project. However, additional feedback was gathered from those key collaborators during a teleconferencing session where the system was presented instead. In Singh & Best (2019), the sanitized real-world dataset comprised transactions sampled over a two-year period between 2014-2016 where feedback was gathered from audit firms, a bank and information systems auditors to evaluate the prototype application. Thus, validation and usefulness of applying link analysis and visualization was achieved via these reviews.

→ **Investigation – Decision Support**

In Han et al. (2018), the data comprised both synthetic and real-world datasets where feedback was gathered from AML practitioners suggesting the proposed system can reduce time and cost by around 30%. Furthermore, the accuracy was also evaluated on some NLP models, where the news SA model achieved 76.96% accuracy, the tweet SA model achieved 63.10% accuracy, and the RE model achieved 88% accuracy when compared to the state-of-the-art.

Advantages

Application Focus	Prevention	Detection		Investigation	
Application Domain	Risk Evaluation	Pattern/Anomaly Discovery	Case Prioritization	Visual Analysis	Decision Support
AI Techniques	DT, Naïve Bayes	SVM, DT, Neural Network, iMST, CBLOF, TEART, Bayesian Network, EM, ANFIS, RF, BLR, Naïve Bayes, IF	DT, LR, Gradient Boosting	Visualization, Link Analysis, Heatmap, Network Analysis	NLP, Link Analysis
Advantages	Understanding of Exposure to Potential Money Laundering; Improved Productivity; Tailor Customer Risk Assessment	Efficient Detection of Hidden Patterns; False-Positives Reduction	False-Alerts Reduction	Interactive Visualization; Global Overview of Trends; Tracking of Movement	Enlightened Decision Making; Investigation Efficiency
	Risk-Based Approach	Transaction Monitoring Approach		Holistic Investigation Approach	

Figure 9. Synthesis of Advantages of Techniques for Application Domains

This section synthesizes the proposed techniques from the selected studies and the identified advantages they provide for the different application domains in AML. This is illustrated in Figure 9 and an extended table is available in Appendix B (see Table 10). The identified advantages were categorized into five main categories – one for each application domain – which was further categorized under three advantageous approaches. Thus, the subsequent text will elaborate further on each of these.

→ Prevention – Risk Evaluation

As aforementioned, prevention refers to the risk management and control approach whereby the application domain risk evaluation covers approaches whose purpose is to evaluate potential risk of money laundering. In this aspect, DTs and Naïve Bayes have been suggested. Therefore, applying these techniques can facilitate a *risk-based approach* within the context of AML by enabling the banks to:

- 1) *Understanding of exposure to potential money laundering* by, for instance, enabling help to determine money laundering transactions and risk ranking. For example, Wang & Yang (2007, p. 283) stated “the risk rank is used to determine the possibility that the customer launder money use the bank products and services.” They further claimed that “Decision tree learning is used to induce a knowledge tree which can help to determine company’s money laundering risk” (Wang & Yang, 2007, p. 286).
- 2) *Improved productivity* by, for instance, improving scalability and enabling simple and effective solutions to determining the risk level on money laundering. For example, Jayasree & Siva Balan (2017, p. 97) stated that the contributions of BIDT comprises “to efficiently determine the company’s money laundering risk and improve the scalability.”
- 3) *Tailor customer risk assessment* by, for instance, assessing the risk of money laundering pertaining to individual customers to implement appropriate controls. For example, Wang & Yang (2007, p. 284) stated “the different categories of customers have different inherent

possibility to carry on money laundering activities,” whereby they claim that “different customers must adopt different AML policies.”

→ **Detection – Patterns/Anomaly Discovery and Case Prioritization**

Furthermore, detection refers to the proactive approach to identify money-laundering activities whereby the application domain pattern/anomaly discovery and case prioritization cover approaches whose purpose is to detect unusual behavior related to money laundering and to prioritize cases for further investigation, respectively. In this aspect, numerous techniques have been suggested as depicted in Figure 9. Therefore, applying these techniques can facilitate a *transaction monitoring approach* within the context of AML by enabling banks to:

- 1) *Efficient detection of hidden patterns* and 2) *False-positives reduction* by, for instance, enabling timely and accurate identification of rare and suspicious transactions. For example, Rocha-Salazar et al. (2021, p. 11) stated that their solution “allows cases of money laundering and terrorist financing to be detected at the right moment in the transaction, preventing illegal resources from being further integrated into the financial system.” Further, Lv et al. (2008, p. 214) claimed that their solution “shows promising results in reducing false positive rate and enhancing detection rate.”
- 3) *False-alerts reduction* by, for instance, enabling alert filtering and prioritization for manual investigation. For example, Jullum et al. (2020, pp. 183-184) stated that they constructed a model for “prioritizing which transactions should be further investigated by AML investigators” while the model is trained to “predict the probability that a new transaction should be reported.” Further, Tertychnyi (2020, p. 53) claimed that the first layer of their model is to “filter out clearly non-illicit customers and at the same time of not miss potentially illicit ones.”

→ **Investigation – Visual Analysis and Decision Support**

Lastly, investigation refers to the investigative approach on money-laundering flagged suspicions whereby the application domain visual analysis and decision support cover approaches whose purpose is to identify relationships of suspicious activities and to facilitate investigative decision making, respectively. In this aspect, visualization and NLP techniques have been suggested. Therefore, applying these techniques can facilitate a *holistic investigation approach* within the context of AML by enabling the banks to:

- 1) *Interactive visualization* by, for instance, providing relevant information pertaining to complex and time-varying data. For example, Chang et al. (2008, p. 64) stated that their approach “assists analysts in exploring large numbers of categorical, time-varying data containing wire transactions.” They further claimed that their solution “provides a highly interactive, exploratory capability for seeing information in context and getting further detail whenever needed” (Chang et al., 2008, p. 74).
- 2) *Global overview of trends* by, for instance, enabling the ability to obtain a clear overview of correlations and, thereby, discover trends. For example, Singh & Best (2019, p. 17) stated that using data visualization techniques “may enhance an investigator’s ability to ‘see’ patterns and efficiently target suspicious ones.” This goes together with the findings in Chang et al. (2008, p. 76) demonstrating that visualization techniques “significantly enhances the analysts’ ability to see global trends,” and that it “allows the analysts to see a complete relationship between accounts, keywords, time, and patterns of activity.”

- 3) *Tracking of Movement* by, for instance, tracing the paths of suspicious transactions within a bank. For example, Singh & Best (2019, p. 5) stated that “link analysis is effective in identifying relationships with several degrees of separation which is particularly useful in tracking the placement, layering, and integration of money as it moves around unexpected sources.”
- 4) *Enlightened decision making* by, for instance, enabling efficient and more accurate decisions to be made by investigators based on additional evidence. For example, Han et al. (2018, p. 37) stated that their proposed solution “provide additional evidence to human investigators for final decision-making.” They further claimed that their solution “can provide different evidence extracted and analyzed from different data sources to facilitate human investigators” (Han et al., 2018, p. 42).
- 5) *Investigation efficiency* by, for instance, enabling effort reduction among investigators. For example, Han et al. (2018, p. 37) stated that their system “can reduce approximately 30% time and cost compared to their [AML practitioners] previous manual approaches of AML investigation.”

5 Discussion and Conclusion

This chapter provides a discussion of the results and concludes the thesis by answering the research question, outlines the research contributions, ethical considerations, and limitations, as well as provides suggestions for future research directions.

5.1 Discussion of the Results

Money laundering is a prevalent concern where the banking industry has been at the forefront of being used for such activities. The crime itself is becoming highly sophisticated and complex, whereby the continuous amplification of its volume increases banks' vulnerability and, simultaneously, threatens the financial stability and international security. Consequently, the application of AI techniques in the fight against money laundering has caught the attention of numerous researchers in recent years. In this thesis, a systematic review of the literature was performed to explore these publications focusing on the banking industry. Thereby, filling a knowledge gap pertaining to additional concentrated and systematic research in this context as indicated by aforementioned literature presented in scientific base (Chen et al., 2018; Leite et al., 2019).

The first sub-question was formulated as follows: *which AI techniques and algorithms are predominantly suggested in the literature, and for which approaches to AML?* aiming to identify different AI techniques used and/or suggested and to identify the AML activities for which these were applied in the literature. The selected publications all focused on approaches, which could be categorized into the five main application domains: risk evaluation, pattern/anomaly discovery, case prioritization, visual analysis, and decision support as to where AI is applied to support this fight. They were further categorized under three focus areas, namely prevention, detection, and investigation. In addition, a number of different techniques were identified for the different approaches to AML where most could be divided into supervised- and unsupervised learning techniques and deep-learning-based NLP techniques while also visualization techniques were captured as depicted in Table 6 and Table 8.

The second sub-question was formulated as follows: *what are the outcomes of the AI-proposed methods?* aiming to learn how the proposed techniques were evaluated, as well as to identify the advantages of the proposed techniques and, thus, the extent to which they can make AML efforts more effective. Evidently, various types of evaluation measures have been applied to evaluate the techniques as depicted in Table 9. Although most studies used real-world datasets, there was a lack of confirmed money laundering cases whereby 'suspicious' behavior had to be modelled in order to evaluate the proposed technique(s). Further, the evaluated techniques put forth a number of advantages they contribute with to the different application domains in the banking sector. The advantages comprise understanding of exposure to potential money laundering, improved productivity, tailor customer risk assessment, efficient detection of hidden patterns, false-positives reduction, false-alerts reduction, interactive visualization, global overview of trends, tracking of movement, enlightened decision making, and investigation efficiency. They were further categorized under risk-based approach, transaction monitoring approach, and holistic investigation approach as to how the proposed techniques can facilitate the fight against money laundering in the banking sector.

The results from both sub-questions shed light on the supporting mechanisms provided by AI in the overall combat against money laundering in the banking sector. Concerning prevention and risk evaluation, the supervised learning techniques DT and Naïve Bayes have been proposed to facilitate a risk-based approach in terms of understanding the exposure to money laundering, enabling simple and effective solutions to determining the risk level on money laundering and tailor customer risk assessment. Concerning detection comprising pattern/anomaly discovery and case prioritization, a mix of supervised- and unsupervised-learning techniques have been proposed to facilitate a transaction monitoring approach in terms of enabling efficient detection of hidden patterns with greater accuracy thereby minimizing false-positives and false-alert reduction, and thereby discovering activities related to money laundering and prioritize further manual investigation amongst the pile of transactions. Concerning investigation comprising visual analysis and decision support, various visualization and deep-learning NLP techniques have been proposed to facilitate a holistic investigation approach in terms of enabling interactive visualization, global overview of trends, tracking of movement of transactions, enlightened decision-making and investigation efficiency, thereby enabling investigators to ‘see’ patterns and identify relationships of suspicious activities as well as enabling a more holistic evidence-based approach while enabling effort reduction among investigators.

Overall, the findings are consistent with previous research following Leite et al. (2019). Although the application domains in this thesis slightly deviated from those found in their research, the result in this thesis showed that most previous studies have focused on the *detection* area and, in particular, the application domain *pattern/anomaly discovery*. This concurs with the findings in Leite et al. (2019) where they acknowledged a majority of publications in their systematic review pertaining to the application domains *detection of suspicious transactions* and the *pattern/group/anomaly/money laundering detection*. This is further supported by the study performed by Chen et al. (2018), where they also found that anomaly detection was popular among the literature. Other application domains captured in the study performed by Leite et al. (2019) was risk assessment/analysis, security, control structuring and/or governance applications, and visual analysis/applications of visual techniques. The reason for the application domains deviating somewhat could be that this thesis focused on the banking sector in particular while the study by Leite et al. (2019) was more general in nature.

Contrary to previous research, the findings in this thesis set forth the aforementioned advantages categorized under the three overarching advantageous approaches using AI techniques for dealing with money laundering in the banking sector, namely risk-based approach, transaction monitoring approach, and holistic investigation approach. Previous reviews did not focus on the supporting aspects enabled by technology in this field in such depth other than some being indicated or otherwise inferences could be made. For instance, Chen et al. (2018) indicated that an AML system facilitates reduction in manual processes comprising screening, which is supported by the findings in this thesis being captured in the risk-based approach. However, by capturing the depth of the supporting aspects enabled by the technology allows for a more practical insight for practitioners. Further, whilst it has been recognized by previous research (Craig, 2019; Han et al., 2018; Tai & Kan, 2019) that conventional solutions to AML are resource-consuming and inefficient at identifying money laundering activity, previous research (Chen et al., 2018; Kurum, 2020) further acknowledged an increasing interest in the application of AI to this field. Since this thesis aimed at providing a holistic view of this from the banking perspective due to scarce research doing so, the results of this thesis show that the advantages from adopting AI spanning multiple application domains in AML augments those conventional solutions by, for instance, improving efficiency and effective use of resources. Thereby, confirming aforementioned knowledge and/or assumptions concerning the potentials of applying AI in this domain.

5.2 Conclusion

In this thesis, the application of AI techniques and how it can support the combat against money laundering in the banking sector was investigated. Hence, the main research question in this thesis was formulated as follows: *how can the combat against money laundering in the banking sector be supported by using AI techniques?* Two sub-questions were formulated as captured in the previous section and an SLR was performed following the the five-stage framework proposed by Wolfswinkel et al. (2013) to answer the research question and achieve the overall aim of the study pertaining to filling a systematic knowledge gap concerning an evidence-based review that rigorously analyzes and synthesizes existing literature in this domain. Consequently, 22 publications were selected and, thus, included in the review.

Although the fight against money laundering is a difficult task, the findings of this thesis indicate a number of ways by which the combat against money laundering in the banking sector can be supported through the application of various techniques spanning multiple application domains as synthesized in Figure 9. Firstly, the reviewed publications all focused on approaches which was categorized into five main application domains and further into three focus areas. Thus, channelling AI techniques into these identified application domains can further strengthen the banks' AML programs by providing valuable support to deal with money launderers. For instance, researchers have applied various AI techniques in order to facilitate a risk-based, transaction monitoring, and holistic investigation approach for dealing with the challenges posed by money launderers. Moreover, examples of advantages it implies are: 1) the overall understanding of the exposure to potential money laundering whereby the implementation of appropriate mitigation control measures is enabled and, thereby, also prevention, 2) the overall efficient detection of hidden patterns and case prioritization whereby timely and accurate identification of suspicious transactions hindering further integration of illegal money as well as alert filtering and prioritization for manual investigation are enabled and, thereby, also detection, and 3) the overall global identification of relationships of suspicious activities and enlightened investigative decision-making whereby the ability to obtain a clear overview of correlations and trends of money movement as well as efficient and more accurate decisions by investigators are enabled and, thereby, also investigation.

Thus, it can be concluded that using AI in the field of AML can support the combat against money laundering in the banking sector in numerous ways. The banks can adopt AI in a wide range of application domains whereby it can be leveraged to augment the different approaches to AML. Thereby, enabling the banks to mitigate risk, detect suspicious activities, and holistically investigate suspicious cases in their growing role to combating money laundering. Although the results show that the development of effective AI techniques underpins AML efforts in the banking sector, it is worth noting that the publications included in the review were dispersed across different countries which could further indicate performance differences of the technique(s) for different countries.

Lastly, the findings of this thesis offer a systematic review for other researchers which could prove to be essential for directing future research to be performed on emphasized gaps in literature in this area while, simultaneously, the findings of this thesis offer practitioners with a knowledge base in terms of an evidence-based overview of relevant techniques in the realm of AML as well as directions concerning appropriate solutions for various application domains. Thereby, constituting theoretical and practical contributions of the findings of the present thesis. In this light, the findings of the present thesis contribute to the overall knowledge base concerning the field of AML from the perspective of the banking sector and, thus, broadening the exploration where less focus has been placed in previous research.

5.3 Ethical and Societal Consequences

The current thesis performed an SLR of current literature and, thereby, did not collect personal nor sensitive information from participants. Thus, the ethical implications are limited to the documents used and the practical influence they might impose. Although the current thesis employed the five-stage framework as presented in Wolfswinkel et al. (2013) for performing a systematic and rigorous literature review to address this, it is rather difficult, or perhaps even impossible, for a study to be entirely bias-free. However, to minimize potential subjective interpretations of literature, the overall procedure for performing the SLR was set in advance as well as with the purpose to seek theoretical saturation during the coding process. Further, unpublished research evidence and other types of findings not made public was not included while backward and forward snowballing was employed to minimize bias perspective and to ensure an exhaustive systematic review. No or low ethical and societal consequences are expected as a result of this thesis. The risk that the findings could be used by money launderers with the intention of benefiting from such knowledge by adapting their techniques accordingly is deemed low considering that the findings are general and not related to particular banking institutions. Further, it is worth mentioning that although technological developments can bring a broad range of opportunities in AML, it is important to 1) note that they can also provide criminals additional sophisticated methods to perform their criminal activities, and 2) consider the impact of data protection compliance.

5.4 Limitations

The steps of the overall SLR were openly documented and presented in the thesis towards enabling reproducible research. Unlike other types of research, such as those employing interviews or other types of methods involving data collection directly from individual participants, the nature of SLRs promotes transparency and reproducibility by following a rather strict protocol. Nevertheless, the reproducible queries may not produce precisely similar search results in future instances due to the possibility of databases being updated. Additional limitations involve the fact that the entire SLR was performed by one person which could have unintended impact on the results and, consequently, the conclusion due to the aforementioned potentials of biases. Although the strategies for mitigating biases, the outcome of the results and, thus, the conclusion could have looked slightly different if two or more researchers were involved in the study selection and analysis where different perspectives would promote the overall objectivity. Similarly, although backward and forward snowballing was employed, the SLR was initially performed using two databases which could indicate that more literature could have been found both in terms of direct search results by the database itself but also in terms of snowballing on those papers if additional databases were included. However, adding additional databases to the data sources would also imply additional time on the SLR search and analysis which would not be ideal owing to the time constraints. Likewise, the chosen search terms and/or formulation of search terms applied in the databases could also impose unintended limitations to the search results by not encompassing all studies that would be relevant for the current thesis. Moreover, considering that most studies were focused on the detection area among the publications included in the SLR further indicate an unequal distribution of the overall supporting impact of AI for the remaining application domains and, consequently, the overall combat against money laundering. Lastly, it is worth noting that differences in legislation among countries further implies differences in money-laundering reporting obligations from authorities for banks. Therefore, using a certain AI technique for a particular application domain may indicate performance differences for different countries.

5.5 Future Research

Although studies on money laundering are ever growing, it is still a novel topic whereby research focusing on money laundering is rather scarce compared to other crimes and is, thus, in need of additional focused studies. Hence, suggestions for future research are provided as follows. First, whilst most studies have been focused on the detection area, continued efforts should extend to other application domains as depicted in Figure 6 and Figure 9 and, thereby, explore and experiment with additional techniques in those areas to produce more literature there. For example, more studies should be performed on the focus area *investigation*, where various techniques supporting AML investigators/analysts in their daily work through *visual analysis* and *decision support* should be explored. Concerning visual analysis, it is suggested that future research focus on the integration of AI and visualization in AML where feedback could be gathered directly from investigators/analysts to evaluate the solution. Further, considering differences in legislation among countries, future research could conduct a comparative study to measure the extent to which it could impact the performance of a certain AI technique applied in an AML domain. This could be performed by evaluating the same technique using datasets from different banks operating in different countries. Lastly, an interesting study would be to examine the potential cost effectiveness of applying AI solutions in the AML domain in the banking industry, which could be performed through a case study.

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Appendix A – Systematic Literature Review

~ 1 st ELSEVIER SCOPUS ~				
Search field: Title, abstract and keywords				
Search terms:				
(TITLE-ABS-KEY (({money laundering} OR {fight money laundering} OR {fight against money laundering} OR {combat money laundering} OR {combating combat money laundering} OR {prevent money laundering} OR {money laundering prevention} OR {detect money laundering} OR {money laundering detection} OR {anti-money laundering}))) AND TITLE-ABS-KEY (({artificial intelligence} OR {artificial intelligence techniques} OR {artificial intelligence algorithms} OR {AI} OR {AI techniques} OR {AI algorithms} OR {data science} OR {machine learning} OR {supervised} OR {unsupervised} OR {natural language processing} OR {expert systems} OR {data visualization} OR {deep learning} OR {classification} OR {robotics} OR {automation}))) AND TITLE-ABS-KEY (({approach} OR {activity} OR {method} OR {framework} OR {domain} OR {process})) OR ({banking sector} OR {banking industry} OR {banking} OR {bank} OR {transaction}))) AND (LIMIT-TO (LANGUAGE , "English"))				
Total articles retrieved: 144				
Duplicates removed: 1		Sample refined (title & abstract): 104		Sample refined (full text): 28
Code	Total articles included: 11			
Year	Author(s)	Title	Publication	Reason(s) for its selection
C1.1	Chang et al.	Scalable and interactive visual analysis of financial wire transactions for fraud detection	Information Visualization	The article fulfils the inclusion criteria. The paper proposes visualizations techniques for AML.
C1.2	Lv et al.	A RBF Neural Network Model for Anti-Money Laundering	Proceedings of the 2008 International Conference on Wavelet Analysis and Pattern Recognition	The article fulfils the inclusion criteria. The paper proposes an RBF neural network model for AML.
C1.3	Keyan & Tingting	An Improved Support-Vector Network Model for Anti-Money Laundering	2011 International Conference on Management of e-Commerce and e-Government	The article fulfils the inclusion criteria. The paper focuses on SVM model for AML.
C1.4	Han et al.	NextGen AML: Distributed Deep Learning based Language Technologies to Augment Anti Money Laundering Investigation	Proceedings of the 56 th Annual Meeting of the Association for Computational Linguistics-System Demonstrations	The article fulfils the inclusion criteria. The paper focuses on deep learning based NLP to improve AML investigations.
C1.5	Singh & Best	Anti-Money Laundering: Using data visualization techniques to identify suspicious activity	International Journal of Accounting Information Systems	The article fulfils the inclusion criteria. Focus on data visualization techniques for identifying money laundering activities.
C1.6	Zhang & Trubey	Machine Learning and Sampling Scheme: An Empirical Study of Money Laundering Detection	Computational Economics	The article fulfils the inclusion criteria. Studies machine learning algorithms in laundering detection.
C1.7	Islam & Nasir	Evaluation of money laundering risk of bank accounts using Naïve Bayes Classification	Journal of Engineering Science and Technology	The article fulfils the inclusion criteria. The study focuses on Naïve Bayes Classification for risk evaluation of bank accounts.
C1.8	Jullum et al.	Detecting money laundering transactions with machine learning	Journal of Money Laundering Control	The article fulfils the inclusion criteria. The study focuses on a machine learning model for suspicious transactions in a bank.
C1.9	Shokry et al.	Counter Terrorism Finance by Detecting Money Laundering Hidden Networks Using Unsupervised Machine Learning Algorithm	International Conference ISC, Society, and Human Beings 2020	The article fulfils the inclusion criteria. The paper proposed an unsupervised machine learning technique for the detection of money laundering.

C1.10 2020	Tertychnyi et al.	Scalable and Imbalance-Resistant Machine Learning Models for Anti-Money Laundering: A Two-Layered Approach	FinanceCom 2020	The article fulfils the inclusion criteria. The paper proposed a two-layered approach for the detection of money laundering.
C1.11 2021	Rocha-Salazar et al.	Money laundering and terrorism financing detection using neural networks and an abnormality indicator	Expert Systems with Applications	The article fulfils the inclusion criteria. Proposes a model improving detection of money laundering.
Comment: Reasons for the exclusion of articles was mainly due to focus of the topic being on something different compared to the present thesis, only a small part of the inclusion criteria being fulfilled, and/or due to the choice of methodology (i.e., reviews). The chosen articles above makes the start set for applying the forward and backward snowballing, which is conducted below.				
~ ROUND 1 ~				
Forward snowballing: 185				
Duplicates removed: 39		Sample refined (title & abstract): 125		Sample refined (full text): 21
Code	Total articles included: 0			
Year	Author(s)	Title	Publication	Reason(s) for its selection
-	-	-	-	-
Comment: Reasons for the exclusion of articles was due to the article not being available in full text and/or in English, and/or the focus of the topic being on something else compared to the present thesis. Thus, lack of adhering to the inclusion criteria of the present thesis. Other main reasons for the exclusion of articles were due to duplicates and the citation tracking also providing, for instance, other reviews, books, and/or theses. The citation tracking was performed by searching for the particular article included in the start set in Google Scholar.				
Backward snowballing: 348				
Duplicates removed: 52		Sample refined (title & abstract): 261		Sample refined (full text): 33
Code	Total articles included: 2			
Year	Author(s)	Title	Publication	Reason(s) for its selection
C1.7 2016	Jayasree & Siva Balan	Money laundering regulatory risk evaluation using Bitmap Index-based Decision Tree	Journal of the Association of Arab Universities for Basic and Applied Sciences	The article fulfils the inclusion criteria. The paper proposed a technique for evaluation of risk factor within AML.
C1.11 2014	Heidarinia et al.	An Intelligent Anti-Money Laundering Method for Detecting Risky Users in the Banking Systems	International Journal of Computer Applications	The article fulfils the inclusion criteria. The study proposes a fuzzy system to detect suspicious accounts.
Comment: Reasons for the exclusion of articles was due to the article not being available in full text and/or in English, and/or the focus of the topic being on something else compared to the present thesis. Thus, lack of adhering to the inclusion criteria of the present thesis. Other main reasons for the exclusion of articles were due to duplicates and the reference tracking also providing, for instance, other reviews, books, and/or theses. The included articles from the forward and backward snowballing above makes the start set for applying a second round of the snowball sampling performed below.				
~ ROUND 2 ~				
Forward snowballing: 42				
Duplicates removed: 16		Sample refined (title & abstract): 24		Sample refined (full text): 2
Code	Total articles included: 0			
Year	Author(s)	Title	Publication	Reason(s) for its selection
-	-	-	-	-
Comment: Reasons for the exclusion of articles was similar to the aforementioned reasons. Thus, lack of adhering to the inclusion criteria of the present thesis. The citation tracking was performed by searching for the particular article included in the start set in Google Scholar.				
Backward snowballing: 34				
Duplicates removed: 11		Sample refined (title & abstract): 22		Sample refined (full text): 1
Code	Total articles included: 0			
Year	Author(s)	Title	Publication	Reason(s) for its selection
-	-	-	-	-
Comment: Reasons for the exclusion of articles was similar to those aforementioned. Thus, lack of adhering to the inclusion criteria of the present thesis. Since no articles were included from neither the forward snowballing nor the backward snowballing during this second round of snowball sampling, it sets the end of this iteration from this particular database.				

~ 2nd IEEE XPLORE ~

Search field: Title, abstract and keywords

Search terms:

((("Abstract": "money laundering" OR "fight money laundering" OR "combat money laundering" OR "prevent money laundering" OR "anti-money laundering" OR "Document Title": "money laundering" OR "fight money laundering" OR "combat money laundering" OR "prevent money laundering" OR "anti-money laundering" OR "Author Keywords": "money laundering" OR "fight money laundering" OR "combat money laundering" OR "prevent money laundering" OR "anti-money laundering") AND ("Abstract": "artificial intelligence" OR "machine learning" OR "techniques" OR "algorithms" OR "unsupervised" OR "supervised" OR "systems" OR "automation" OR "Document Title": "artificial intelligence" OR "machine learning" OR "techniques" OR "algorithms" OR "unsupervised" OR "supervised" OR "systems" OR "automation" OR "Author Keywords": "artificial intelligence" OR "machine learning" OR "techniques" OR "algorithms" OR "unsupervised" OR "supervised" OR "systems" OR "automation") AND ("Abstract": "bank" OR "transaction" OR "detection" OR "Document Title": "bank" OR "transaction" OR "detection" OR "Author Keywords": "bank" OR "transaction" OR "detection"))

Total articles retrieved: 80

Duplicates removed: 7

Sample refined (title & abstract): 41

Sample refined (full text): 28

Total articles included: 4				
Code Year	Author(s)	Title	Publication	Reason(s) for its selection
C2.1 2005	Tang & Yin	Developing an Intelligent Data Discriminating System of Anti-Money Laundering Based on SVM	Proceedings of the Fourth International Conference on Machine Learning and Cybernetics	The article fulfils the inclusion criteria. The study proposes algorithms based on SVM for AML.
C2.2 2007	Wang & Yang	A Money Laundering Risk Evaluation Method Based on Decision Tree	Proceedings of the Sixth International Conference on Machine Learning and Cybernetics	The article fulfils the inclusion criteria. The study proposes a decision tree method for risk evaluation in AML.
C2.3 2009	Zengan	Application of Cluster-Based Local Outlier Factor Algorithm in Anti-Money Laundering	2009 International Conference on Management and Service Science	The article fulfils the inclusion criteria. The focus of this particular study aims at proposing a cluster-based local outlier factor algorithm for AML.
C2.4 2014	Chen et al.	Exploration of the effectiveness of expectation maximization algorithm for suspicious transaction detection in anti-money laundering	2014 IEEE Conference on Open Systems	The article fulfils the inclusion criteria. The study proposes employing Expectation Maximization for AML.

Comment: Reasons for the exclusion of articles was mainly due to focus of the topic being on either something different compared to the present thesis or not niched enough to the focus of the present thesis, due to only a small part of the inclusion criteria being fulfilled, and/or due to the choice of methodology (i.e., reviews). The chosen articles above makes the start set for applying the forward and backward snowballing, which is conducted below.

~ ROUND 1 ~

Forward snowballing: 219

Duplicates removed: 78

Sample refined (title & abstract): 116

Sample refined (full text): 20

Total articles included: 5				
Code Year	Author(s)	Title	Publication	Reason(s) for its selection
C2.1 2009	Wang & Dong	Research on Money Laundering Detection based on Improved Minimum Spanning Tree Clustering and Its Application	2009 Second International Symposium on Knowledge Acquisition and Modeling	The article fulfils the inclusion criteria. The study proposes clustering to detect money laundering.
C2.2 2011	Larik & Haider	Clustering based Anomalous Transaction Reporting	Procedia Computer Science	The article fulfils the inclusion criteria. The study proposes a hybrid anomaly detection approach in the context of AML.
C2.1 2011	Raza & Haider	Suspicious activity reporting using dynamic Bayesian networks	Procedia Computer Science	The article fulfils the inclusion criteria. The study proposes clustering in AML.
C2.1 2013	Khan et al.	A Bayesian Approach for Suspicious Financial Activity Reporting	International Journal of Computers and Applications	The article fulfils the inclusion criteria. The study proposes Bayesian network in AML.

C2.2 2020	Kumar et al.	Anti-Money Laundering detection using Naïve Bayes Classifier	2020 IEEE International Conference on Computing, Power and Communication Technologies	The article fulfils the inclusion criteria. The study proposes text analytics and Naïve Bayes classifier to identify money laundering activities.
Comment: Reasons for the exclusion of articles was due to the article not being available in full text and/or in English, and/or the focus of the topic being on something else compared to the present thesis. Thus, lack of adhering to the inclusion criteria of the present thesis. Other main reasons for the exclusion of articles were due to duplicates and the citation tracking also providing, for instance, other reviews, books, and/or theses. The citation tracking was performed by searching for the particular article included in the start set in Google Scholar. The included article above makes the start set for applying a second round of the forward and backward snowballing, which is conducted below.				
Backward snowballing: 46				
Duplicates removed: 14		Sample refined (title & abstract): 30		Sample refined (full text): 2
Code	Total articles included: 0			
Year	Author(s)	Title	Publication	Reason(s) for its selection
-	-	-	-	-
Comment: Reasons for the exclusion of articles was due to the article not being available in full text and/or in English, and/or the focus of the topic being on something else compared to the present thesis. Thus, lack of adhering to the inclusion criteria of the present thesis. Other main reasons for the exclusion of articles were due to duplicates and the reference tracking also providing, for instance, other reviews, books, and/or theses. Hence, no articles were found adhering to the inclusion criteria in order to be included in the sample.				
~ ROUND 2 ~				
Forward snowballing: 125				
Duplicates removed: 57		Sample refined (title & abstract): 56		Sample refined (full text): 12
Code	Total articles included: 0			
Year	Author(s)	Title	Publication	Reason(s) for its selection
-	-	-	-	-
Comment: Reasons for the exclusion of articles was due to the article not being available in full text and/or in English, and/or the focus of the topic being on something else compared to the present thesis. Thus, lack of adhering to the inclusion criteria of the present thesis. Other main reasons for the exclusion of articles were due to duplicates and the citation tracking also providing, for instance, other reviews, books, and/or theses. The citation tracking was performed by searching for the particular article included in the start set in Google Scholar. The included article above makes the start set for applying a third round of the forward and backward snowballing, which is conducted below.				
Backward snowballing: 83				
Duplicates removed: 35		Sample refined (title & abstract): 40		Sample refined (full text): 8
Code	Total articles included: 0			
Year	Author(s)	Title	Publication	Reason(s) for its selection
-	-	-	-	-
Comment: Reasons for the exclusion of articles was due to the article not being available in full text and/or in English, and/or the focus of the topic being on something else compared to the present thesis. Thus, lack of adhering to the inclusion criteria of the present thesis. Other main reasons for the exclusion of articles were due to duplicates and the reference tracking also providing, for instance, other reviews, books, and/or theses. Considering that no articles were included from neither the forward snowballing nor the backward snowballing during this second round of snowball sampling, it sets the end of this iteration from this particular database.				

Appendix B – Data Analysis

The table below lists the application domains that appeared during the analysis of the studies included in the systematic literature review:

Table 7. Application Domains SQ1

Selective Coding	Axial Coding	Open Coding	Author(s)
Prevention	Risk Evaluation	Risk Rank Customer Assessment Risk Evaluation Risk Determination Risk Judgement Risk Rules Risk Analysis Risk Identification	Wang & Yang (2007) Jayasree & Siva Balan (2017) Islam & Nasir (2020)
Detection	Patterns/Anomaly Discovery	Unusual Behaviour Pattern Recognition Suspicious Activity Track Activity Detect Suspiciousness Outlier Measurement Detect Anomalies Pattern Deviation Behaviour Detection	Tang & Yin (2005) Lv et al. (2008) Wang & Dong (2009) Zengan (2009) Keyan & Tingting (2011) Larik & Haider (2011) Raza & Haider (2011) Khan et al. (2013) Chen et al. (2014) Heidarinia (2014) Zhang & Trubey (2019) Kumar et al. (2020) Shokry et al. (2020) Rocha-Salazar et al. (2021)
	Case Prioritization	Investigation Prioritization Transaction Discrimination Predictive Modelling	Jullum et al. (2020) Tertychnyi et al. (2020)
Investigation	Visual Analysis	Visual Analysis Discover Relationships Behaviour Detection	Chang et al. (2008) Singh & Best (2019)
	Decision Support	Recommendation System Support Investigators Evidence Collection	Han et al. (2018)

The table below lists the techniques that appeared during the analysis of the studies included in the systematic literature review:

Table 8. Technique Categorization SQ1

Technique Categorization	Application/Learning Type	Technique/Algorithm	Author(s)	
Artificial Intelligence (Machine Learning/Natural Language Processing)	Supervised Learning (Classification)	Decision Tree	Wang & Yang (2007)	
		Decision Tree	Jayasree & Siva Balan (2017)	
		Naïve Bayes	Islam & Nasir (2020)	
				<i>Prevention - Risk Evaluation</i>
	Supervised Learning (Classification)	Gradient Boosting	Jullum et al. (2020)	
		Logistic Regression	Tertychnyi et al. (2020)	
		Gradient Boosting		
				<i>Detection - Case Prioritization</i>
	Supervised Learning (Classification)	Support Vector Machine	Tang & Yin (2005)	
		Support Vector Machine	Keyan & Tingting (2011)	
Support Vector Machine		Zhang & Trubey (2018)		
Decision Tree				
Random Forest				
Artificial Neural Network				
Bayes Logistic Regression				
Neural Network		Lv et al. (2008)		
Bayesian Network		Khan et al. (2013)		
Artificial Neural Network		Heidarinia (2014)		
Naïve Bayes	Kumar et al. (2020)			
			<i>Detection - Patterns/Anomaly Discovery</i>	
Unsupervised Learning (Clustering/Outlier Detection)	Isolation Forest	Shokry et al. (2020)		
	One Class Support Vector Machine			
	Improved Minimum Spanning Tree	Wang & Dong (2009)		
	Cluster-Based Local Outlier Factor	Zengan (2009)		
	Transformed Euclidean Adaptive Resonance Theory	Larik & Haider (2011)		
	Dynamic Bayesian Network	Raza & Haider (2011)		
	Expectation Maximization	Chen et al. (2014)		
	Neural Network	Rocha-Salazar et al. (2021)		
Fuzzy Logic				
			<i>Detection - Patterns/Anomaly Discovery</i>	
Visualization	Visualization	Chang et al. (2008)		
	Network Analysis			
	Heatmap			
	Visualization	Singh & Best (2019)		
			<i>Investigation - Visual Analysis</i>	
Deep Learning	Sentiment Analysis	Han et al. (2018)		
	Entity Recognition			
	Relation Extraction			
	Entity Linking			
	Link Analysis			
			<i>Investigation - Decision Support</i>	

The table below lists the dataset and evaluation measures used by the authors of the studies included in the systematic literature review:

Table 9. Evaluation Measures and Dataset SQ2

Application Focus	Application Domain	Dataset	Evaluation Measures	Technique(s)	Author(s)
Prevention	Risk Evaluation	RD	Effectiveness	Decision Tree	Wang & Yang (2007)
		SD, PD (Statlog German Credit Data from the UCI repository)	AR, TPR, FPR, RIT	Decision Tree	Jayasree & Siva Balan (2017)
		SD	Acc, TPR, FPR, Pr, Recall, F-Measure	Naïve Bayes	Islam & Nasir (2020)
Detection	Patterns/Anomaly Discovery	RD	FPR, DR	SVM	Tang & Yin (2005)
		RD	FPR, DR	Neural Network	Lv et al. (2008)
		RD	Anomaly Degree	iMST	Wang & Dong (2009)
		RD, SD	LOF	CBLOF	Zengan (2009)
		RD	Acc, FPR, DR	SVM	Keyan & Tingting (2011)
		RD	AICAF	TEART	Larik & Haider (2011)
		RD	Acc	Bayesian Network	Raza & Haider (2011)
		RD	Bayes Score	Bayesian Network	Khan et al. (2013)
		RD	Acc	EM	Chen et al. (2014)
		SD	Acc	ANFIS	Heidarinia (2014)
		RD	AUC, Regression Analysis	SVM, DT, Neural Network, RF, BLR	Zhang & Trubey (2019)
		SD	Acc	Naïve Bayes	Kumar et al. (2020)
		SD	Domain Experts, Time, Acc	SVM, IF	Shokry et al. (2020)
		RD	Acc, ERR, BERR	Neural Network	Rocha-Salazar et al. (2021)
		Investigation	Case Prioritization	RD	AUC, Brier Score, PPP
	RD		AUPRC	LR, Gradient Boosting	Tertychnyi et al. (2020)
Investigation	Visual Analysis	RD	Case Study	Visualization	Chang et al. (2008)
		RD	Case Study	Network Analysis, Heatmap Visualization, Link Analysis	Singh & Best (2019)
	Decision Support	SD, RD	Acc, Case Study	Sentiment Analysis Entity Recognition Relation Extraction Entity Linking Link Analysis	Han et al. (2018)

SD = Synthetic Dataset | RD = Real Dataset | PD = Public Dataset

AR = Adaptability Rate | TPR = True Positive Rate | FPR = False Positive Rate | Pr = Precision

RIT = Risk Identification Time | Acc = Accuracy | DR = Detection Rate | LOF = Local Outlier Factor

AICAF = Anomaly Index Computation based on Amount and Frequency | AUC = Area Under the Curve

ERR = Error Rate | BERR = Balanced Error Rate | PPP = Proportion of Positive Predictions

AUPRC = Area Under the Precision-Recall Curve

The table below lists the advantages that appeared during the analysis of the studies included in the systematic literature review:

Table 10. Advantages SQ2

Advantage Selective Coding	Advantage Axial Coding	Advantage Open Coding	Techniques	Author(s)
Risk-Based Approach	Understanding of Exposure to Potential Money Laundering; Improved Productivity; Tailor Customer Risk Assessment	Help determine money laundering risk rank of customers; Simple and effective; Customer assessment; Risk ranking; Help determine money laundering risk; Improve scalability; Effectively access large databases; Efficiently determine money laundering risk; Effective evaluation of risk factor; Minimize money laundering cases; Find risk level of a customer	DT	Wang & Yang (2007)
			DT Naïve Bayes	Jayasree & Siva Balan (2017) Islam & Nasir (2020)
<i>Prevention - Risk Evaluation</i>				
Transaction Monitoring Approach	Efficient Detection of Hidden Patterns; False-Positives Reduction	Determine behaviour; Detection of unusual discovery; Improve false positives; Reduce false positives; Suspicious transaction detection; Improve detection rate; Improve identification; Identifies rare activities; Identify suspicious transactions; Determine behaviour; Reduce false positives; Accuracy of suspicious detection; Efficient Detection; Address the rare event problem; False positives reduction; Increased accuracy	SVM SVM SVM DT RF ANN BLR Neural Network Bayesian Network ANN Fuzzy Logic Naïve Bayes IF One Class SVM iMST CBLOF TEART DBN EM Neural Network Fuzzy Logic	Tang & Yin (2005) Keyan & Tingting (2011) Zhang & Trubey (2018) Lv et al. (2008) Khan et al. (2013) Heidarinia (2014) Kumar et al. (2020) Shokry et al. (2020) Wang & Dong (2009) Zengan (2009) Larik & Haider (2011) Raza & Haider (2011) Chen et al. (2014) Rocha-Salazar et al. (2021)
			<i>Detection - Patterns/Anomaly Discovery</i>	
	False-Alerts Reduction	Predict the probability that a new transaction should be reported; Prioritize transactions for manual investigation; Minimize false negatives; Filtering; Customer-level prediction	Gradient Boosting LR Gradient Boosting	Jullum et al. (2020) Tertychnyi et al. (2020)
<i>Detection - Case Prioritization</i>				
Holistic Investigation Approach	Interactive Visualization; Global Overview of Trends; Tracking of Movement;	Assist exploring large data; Global overview of data; Improve ability for comparisons; Improve ability to see global trends; Clear overview of trends and correlations; Overview and detail; Scalability; Visual representations enabling tracking of movement of money; Track the movement of money; Demonstrate complex relationships; Discover patterns and trends; Improve ability to see trends	Visualization Network Analysis Heatmap Visualization Link Analysis	Chang et al. (2008) Singh & Best (2019)
			<i>Investigation - Visual Analysis</i>	
	Enlightened Decision-Making; Investigation Efficiency	More efficient and accurate decision-making; Facilitate investigation; Provide additional evidence	Sentiment Analysis Entity Recognition Relation Extraction Entity Linking Link Analysis	Han et al. (2018)
<i>Investigation - Decision Support</i>				

Appendix C – Glossary

Acc	The accuracy rate “is calculated as the total number of correct predictions divided by the total number of observations and expresses how well the model predicts true cases of money laundering” (Rocha-Salazar et al., 2021, p. 10).
AR	The adaptability rate on crime measures “the time taken to adapt changes or update the money laundering service to a higher level at a less interval of time. Higher the adaptability rate, more quickly, the anti-money laundering system is and therefore is said to be more efficient in handling the money laundering operations” (Jayasree & Siva Balan, 2017, p. 101).
AICAF	The anomaly index computation based on amount and frequency “measures the deviation of (a) transaction amount and (b) the frequency of similar types of transactions from the established behavior of the cluster the customer belongs to” (Larik & Haider, 2011, p. 608).
AUC	The area under the curve “is based solely in the ranking of the predictions” (Jullum et al., 2020, p. 181).
BERR	The balanced error rate is measured 1-balanced accuracy, where the latter is “calculated as the average of the true positive and negative rates” (Rocha-Salazar et al., 2021, p. 10).
Brier Score	“The mean squared error of the predicted probabilities compared to the true response” (Jullum et al., 2020, p. 180).
DR	The detection rate definition: “the number of unusual instances by the system divided by the total number of unusual instances presented in the test set” (Yang & Tin, 2005, p. 3457).
ERR	The error rate “is calculated as the number of incorrect predictions divided by the total number of observations and expresses how badly the model predicts cases of money laundering” (Rocha-Salazar et al., 2021, p. 10).
FPR	The false positive rate definition: “the total number of normal instances that are incorrectly classified as unusual divided by the total number of normal instances” (Yang & Tin, 2005, p. 3457).
LOF	The local outlier factor “can be employed to measure the deviant degree of SC [Small Category] points from LC [Large Category], i.e., how far the transactional behavioral patterns represented by the points in SC deviate from the normal or legitimate patterns” (Zengan, 2009, p. 2).
PPP	The proportion of positive predictions “is equal to the proportion of all predictions classified as positive when adjusting the classification threshold such that the TPR [true positive rate] is at a certain level” (Jullum et al., 2020, p. 181).
Pr	Precision “quantifies the number of correct positive predictions made” and “it is calculated as the ratio of correctly predicted positive examples divided by the total number of positive examples that were predicted” (Brownlee, 2020, Precision for Imbalanced Classification section, paras. 1, 3).
TPR	The true positive rate refers to “the measure of genuine customer correctly identified as genuine. It is measured in terms of percentage (%). Higher the true positive rate, the more efficient the method is” (Jayasree & Siva Balan, 2017, p. 100).
Recall	Recall “quantifies the number of correct positive predictions made out of all positive predictions that could have been made,” (Brownlee, 2020, Recall for Imbalanced Classification section, para. 1) and “recall is calculated as the number of true positives divided by the total number of true positives and false negatives” (Brownlee, 2020, Recall for Binary Classification section, para. 1).
RIT	The risk identification time is “the time taken to identify the key values on money laundering accounts in the bank” (Jayasree & Siva Balan, 2017, p. 100).
F-Measure	F-Measure “provides a way to combine both precision and recall into a single measure that captures both properties” (Brownlee, 2020, F-Measure for Imbalanced Classification section, para. 2).