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Transaction monitoring in anti-money laundering: A qualitative analysis and points of view from industry

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ABSTRACT

Financial institutions face significant challenges in their efforts to prevent money laundering and terrorist financing due to criminals' continuously evolving techniques and the vast volume of transactions that need to be processed. The traditional rules-based methods utilised in banks produce high false positive rates, which lead to increased costs and inefficiencies. This study identified the perspectives of 8 anti-money laundering (AML) specialists on the current state and potential improvements in transaction monitoring methods. The results provide in-depth knowledge of the problems and requirements for researchers and practitioners. Semi-structured interviews conducted with the AML experts (totalling 480 min) identified the challenges, requirements for successful implementation, and future trends in transaction monitoring. The findings reveal a growing interest in machine learning and artificial intelligence to enhance the efficiency and accuracy of current approaches. Furthermore, innovative methods such as graph analysis and anomaly detection were suggested to overcome the limitations of rule-based systems. Requirements such as explainability, flexibility, and identifying new risks were extracted and analysed. This research contributes to the existing literature by providing valuable insights from industry experts, guiding the development of advanced transaction monitoring methods, and addressing the disconnect and lack of studies between industries and academicians in the domain.

1. Introduction

Money laundering is a crime that attempts to cover up the source of money and incorporate it into the legal financial system [1]. The rapid expansion of global financial systems and technologies has provided a platform for criminal activities such as money laundering and terrorist financing. A crucial part of anti-money laundering (AML) operations is transaction monitoring, which involves ongoing financial transaction analysis to spot suspicious activity and report it to higher authorities [2]. Financial institutions face many challenges and complexities in transaction monitoring, including high false positive rates, developing money laundering scenarios, and an effective and efficient detection process [3]. Further research is needed to develop enhanced transaction monitoring approaches to prevent crime more efficiently and ease the challenges financial institutions face.

This research involves conducting semi-structured interviews with AML experts. To comprehensively understand the AML field and aid the development of enhanced transaction monitoring methods, three objectives are established: 1. To identify the issues and challenges faced by financial institutions during the transaction monitoring process, 2. To understand the requirements a new transaction monitoring method requires to be adoptable and successful in the industry, and 3. To gather specialists' opinions on potential solutions and the future of the transaction monitoring domain. This study expands upon the work presented by [4].

The novelty of this study lies in its qualitative exploration of transaction monitoring in AML, focusing on in-depth insights from industry experts. It uniquely bridges the gap between academic research and practical industry applications [5], providing a fresh perspective on the challenges, requirements, and future directions in AML strategies. By emphasising the integration of advanced technologies, such as machine learning, the study explored innovative approaches to enhance the accuracy and efficiency of current systems. Furthermore, the paper presents specialist driven forecasts, offering a forward view on the evolution of transaction monitoring in AML, contributing novel viewpoints, and guiding the development of more effective AML practices.

This paper includes a literature review in Section 2, analysing what is already known in the literature regarding the objectives of this study. Section 3 explains the methodology that was employed to conduct this

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research including the use of semi-structured interviews, data analysis, and limitations. The findings and analysis of them are presented in Section 4. Finally, the conclusion is presented in Section 5 summarising the paper.

2. Literature review

This review explores the current literature on the problems and challenges within financial institutions around transaction monitoring, the requirements for new transaction monitoring methods to be adopted and successful in the industry, and future trends and prospects of transaction monitoring. Key problems institutions face and need to resolve include regulatory challenges, data quality issues, high false positives, operational and implementation costs. These issues need to be addressed by financial institutions to effectively detect money launderers. The highlighted requirements in the literature consist of having a scalable approach, reduction in false positives, compliance with regulator's standards, attaining higher accuracy, and flexibility in the method. Future research should consider these requirements when developing a new approach. The literature suggests and is optimistic about the use and adoption of artificial intelligence and machine learning for transaction monitoring. Information sharing and big data analytics are two additional areas that are identified in the literature as future trends and prospects for transaction monitoring.

Financial institutions must comply with the AML regulations. However, institutions find it challenging to keep up and maintain compliance with the constantly evolving regulatory landscape and lack of international standards in transaction monitoring [6]. Poor data quality has also been mentioned as a challenge for transaction monitoring in the literature. Inaccurate and incomplete data can impede the transaction monitoring methods' effectiveness [7]. Data issues can result in high false positive rates, impacting the institution's ability to detect suspicious activity. The high rates of false positives generated are a major problem for financial institutions. The false positive alerts lead to a vast amount of investigations which increase the institution's costs, putting pressure on banks to improve the efficiency and effectiveness of their monitoring methods [8]. Implementation challenges of new transaction monitoring methods are also identified in the literature. Data privacy and protection is one area that makes implementation difficult as systems require the collection and sharing of personal and financial data when implementing a new method [9]. Additionally, the rapid pace of technological advancements along with banks' older technological systems makes it difficult to adapt and implement new solutions effectively [10]. The cost of implementing a new monitoring system will also make it challenging for institutions, especially for smaller institutions with limited budgets and resources [11,12]. In addition, the changing of criminal techniques was identified as a challenge for institutions as the current monitoring methods struggle to keep up with the changes. The existing transaction monitoring methods need to be continuously updated and improved (e.g. creating new rules and scenarios) which is complex and costly to the organisation [11]. Another challenge identified is monitoring cross-border transactions due to the varying regulatory requirements and standards across jurisdictions [9]. Effective monitoring requires collaboration between financial institutions and regulators [13].

Accuracy is a major area that transaction monitoring methods need to improve and therefore a key requirement. Improving the detection accuracy will be a crucial element when measuring the adoptability and success of a new transaction monitoring method [14]. A system with higher accuracy can minimise the number of false positives being generated which is another requirement as it is a huge problem. Scalability is also a requirement for a new transaction monitoring method to handle the rising volume of data given the increasing size and complexity of transactions in financial institutions [15]. A new method should be capable of horizontal and vertical scaling to ensure the approach can expand with demand [16]. Adaptability to address new types of money laundering and terrorist financing should be implemented in a new transaction monitoring method to be deemed successful [14]. The requirement of adaptability can reduce regulatory pressures and prevent reputational damage. Another requirement for a transaction monitoring method to be adoptable is easy implementation into the institutions. The method must integrate with existing systems and require minimal training for end-users [17]. This will allow for a smooth transition from the current approaches to more sophisticated and enhanced methods. The cost-effectiveness of the method is also identified as a requirement, a positive return on investment should be shown to justify its implementation [18]. A new method should reduce investigational and operational costs that arise from the large number of false positive alerts generated, which leads to hiring more employees [19]. Complying with regulations is another important requirement of a new transaction monitoring method. An institution must ensure that the method they implement is up to date with the regulations and must be continuously updated with the evolving regulatory requirements [17]. A risk-based approach is a regulatory requirement for a new method. The method should be customisable to address institution-specific risks and prioritise high-risk customers and industries [20].

The future of transaction monitoring will likely include artificial intelligence and machine learning. In the recent literature, the application of artificial intelligence and machine learning has gained considerable interest in transaction monitoring. Incorporating new and innovative solutions can improve the existing methods in the industry by increasing the accuracy and efficiency of detecting suspicious transactions [21]. Many researchers argue that these innovative solutions will become a crucial component of the future of AML. The existing literature also discusses future AML efforts to collaborate and share information between financial institutions, law enforcement agencies, and regulators [22]. Sharing data can improve accuracy and enhance the detection of money launderers by giving institutions a more comprehensive view of customer behaviour across multiple institutions. Sharing information and data can also lead to developing superior and standardised processes for transaction monitoring [23]. The increasing availability of big data and advanced analytics is another area that is expected to affect the transaction monitoring domain in the future [24]. Institutions can leverage big data to enable the adopting of machine learning and enhance transaction monitoring solutions.

3. Research methodology

This study adopts qualitative research by conducting semi-structured interviews with AML specialists. The overall aim of the study is to provide the field of research with a greater understanding of the transaction monitoring domain to aid in developing a new transaction monitoring approach. In this study, a qualitative approach is taken as a quantitative approach can be limiting in investigating the complexities of the transaction monitoring domain, such as understanding the contextual factors and nuances that may influence the development of a new approach [25]. Qualitative research can provide a deeper and more thorough insight into the opinions, knowledge, and experience of the transaction monitoring specialists [26]. Given that the research is exploratory in nature, utilising a qualitative research design will enable the gathered data to speak for itself. This study contributes to the literature by addressing the gap that currently exists between academia and industry on the transaction monitoring domain. Furthermore, it provides the requirements that a new transaction monitoring method needs to be useful and successful in the industry, from the specialists' points of view [27].

3.1. Research process

Despite the specialised nature of transaction monitoring and the challenges of finding individuals who meet the required criteria, purposive sampling was applied [28]. Specifically, the authors reached out

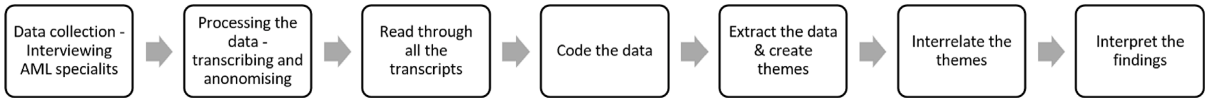

Fig. 1. The Methodology Process.

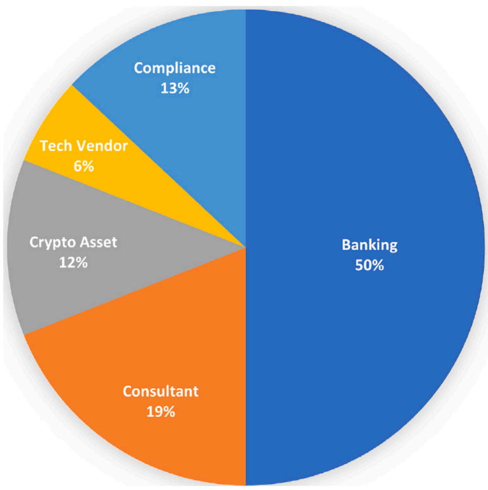

Fig. 2. Interviewees experience in different domains.

Table 1
Interviewees' years of experience in the AML domain.

Years of experience	Total	Percentage
≤ 9	1	12.50%
10–19	5	62.5%
20–29	1	12.50%
30–39	1	12.50%
Total	8	100%

to professionals with a significant background in transaction monitoring, having worked in this field for a minimum of nine years. This method enabled the identification of professionals with the required level of expertise in transaction monitoring, who could provide valuable insights and perspectives on the subject matter. The selection of interviewees took into account their representativeness, determined by their expertise in the field of AML, as well as, their experience within the banking sector. Also, their relevance, based on their knowledge of transaction monitoring, and their willingness and availability to participate were taken into consideration. This approach generated a group of specialists with the necessary characteristics to investigate the transaction monitoring domain to provide a greater understanding of the field and aid in developing a new transaction monitoring approach. The study's objectives were explained to potential participants and an information sheet outlining the study's parameters was provided. The 8 participants were required to complete and sign a participation agreement form to be included in the research. All relevant information and documentation were shared via email. Before the interview sessions, participants were instructed to review the interview scripts to become acquainted with the questions. During the interviews, participants were encouraged to express their perspectives and insights without any influence or bias. The saturation approach was employed to determine the sample size. New data, in the form of semi-structured interviews, was collected until no new information or insights were generated. Once the point of saturation was reached, data collection was concluded, as the data already obtained was deemed sufficient to answer the research question. Fig. 1 presents the complete process of the methodology.

3.2. Data collection techniques

This study used an inductive research approach and therefore employed semi-structured interviews as the data collection technique [29]. The inductive research approach was chosen and utilised due to its capacity to examine the patterns and behaviours of domain experts, and to develop theories about the participants that connect to the paper's objectives [30]. Semi-structured interviews were selected because they can be a valuable tool for researchers in the transaction monitoring domain, as they allow for an in-depth understanding of the participant's experiences, opinions, and knowledge related to the subject [31]. Table 1 shows interviewees' years of experience in the AML domain. This method allows for follow-up questions and exploration of areas in more detail, providing a more nuanced understanding. Participants can share their perspectives and provide insights that the researcher may not have previously considered, identifying potential blind spots and generating new ideas. The interviews lasted approximately 60 min and were conducted online. Once all the interviews were complete the data was transcribed and anonymised for data analysis to then take place. The data collected was comprehensive while avoiding over-reliance on excessive sample size.

3.3. Data analysis

This study refers to [32] for the data analysis process. The data analysis process began with an initial review of all the data, which provided an overall understanding of the information and an opportunity for reflection on its meaning, depth, and potential use. Fig. 2 highlights the interviewees experience across various domains, with most specialists having experience in multiple industries. Table 1 presents the interviewees years of experience within the AML domain. The next step involved coding, which entailed organising the data into labelled categories using the AML experts' language. The researchers adopted an inductive coding approach, a bottom-up method of data analysis that identifies patterns and themes from the data itself. This approach was chosen for its ability to explore new ideas and concepts previously unconsidered. It also provides flexibility and adaptability in the analysis process, helping to minimise researcher biases. Following the coding process, the researchers generated descriptions and themes, which were then used to develop complex analysis layers by interconnecting themes. Finally, the findings of the analysis were represented visually (Fig. 3) and by a detailed discussion of several themes.

3.4. Limitations

The study included a limited number of participants due to time constraints and the difficulty of acquiring participants with the relevant skills and knowledge. Hence, the data may not represent the entire AML and transaction monitoring domain which could limit the findings. Another limitation is the reliance on the author's interpretations and analysis of the data which can cause subjectivity in the findings. Future work should attempt to gather a larger number of specialist participants to gain a better understanding of the transaction monitoring domain. Also, more research is required to reach conclusive decisions on topics such as the requirements of a new transaction monitoring method as the author's perspectives have been presented.

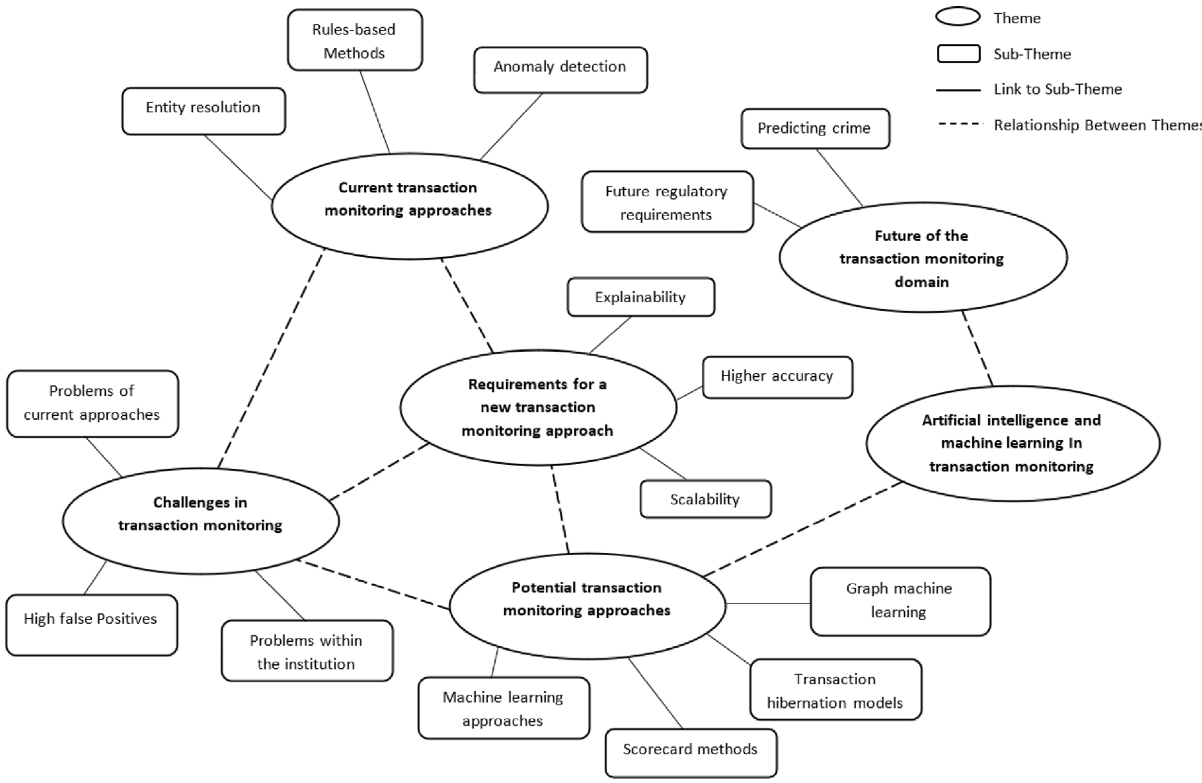

Fig. 3. Relationship between themes and sub-themes.

4. Findings and discussion

This section presents the results of the semi-structured interviews conducted with AML specialists. The findings are themed into six areas: Current transaction monitoring approaches, Challenges in transaction monitoring, Artificial intelligence and machine learning in transaction monitoring, Requirements, Future of the domain, and Transaction monitoring approaches. A comprehensive analysis of the interviews, complemented by direct quotations from the specialists, is provided in tabular format. The tables also include the coding and thematic classification of the quotes, providing a clear and organised presentation of the data. An in-depth discussion and interpretation of the findings are conducted to better understand the implications of these insights for the transaction monitoring domain. The relationship between the different themes and various relevant sub-themes is presented in Fig. 3.

Table 2
Quotes of interviewees on the current transaction monitoring methods in the industry.

	What are the current transaction monitoring methods used in the industry?
1	*'So currently we heavily use rule-based systems, with scenario-based rules, where you alert if something is triggered'*
2	*"Mainly rules-based methods and a lot of statistical analysis is done to understand where it's appropriate to set thresholds"*
3	*"We have started to try and detect anomalies in customer's behaviours at the transactional level. So, we're attempting to look for indications of financial crime, trialing machine learning"*
4	*"A rules-based method, mostly a vendor solution. Generally, it's going to be one that has a library you can pick and choose from, ones which allow you to build rules"*
5	*"Most of our solution is based on rules but we do incorporate a bit of entity resolution and network analysis"*

4.1. Current transaction monitoring approaches

The findings from the semi-structured interviews with transaction monitoring specialists suggest that currently, the industry is heavily reliant on rule-based systems for detecting money laundering and terrorist financing, which agrees with the current literature [33–36]. Table 2 shows some quotes from the interviewees. All interviewees in this study stated the use of rules-based transaction monitoring within their institution. The rule-based approach is based on scenario-based rules that trigger alerts when a particular event occurs. Along with the rules-based methods, a lot of statistical analysis is conducted to set thresholds for the systems which is a very complex and time-consuming task for institutions [37].

While some banks add supplementary tools to the existing method, the majority of solutions still rely solely on the rule-based method. For instance, some institutions are incorporating entity resolution and network analysis with the help of external companies to enhance their transaction monitoring approach. Although external companies improve the current approaches there are still inefficiencies, due to the fact it is being used with rules-based methods, as mentioned by a specialist.

In contrast, an interviewee who operates as the Head of Financial Crime Detection at a large banking institution revealed that they have started testing and incorporating machine learning, adding to the rule-based monitoring approach. Machine learning is being examined to detect anomalies in customer behaviour at the transactional level, allowing them to search for indications of money laundering and terrorist financing.

One of the AML specialists described the anomaly detection process by comparing it to searching for a needle in a haystack. Instead of looking for the needles in the haystack like traditional approaches, the institution defines what normal looks like and flags transactions that deviate from it. This approach utilises the vast amount of normal transaction data that the bank possesses (92 petabytes). However, when developing this approach the institution needs to be extremely cautious of including illegal transactions in the group of normal transactions, as this could lead to criminals avoiding detection. Overall, the findings suggest that while rule-based methods, sometimes enhanced by

Table 3
Quotes on the problems and challenges financial institutions face with current transaction monitoring methods.

	What are the problems and challenges of current transaction monitoring methods?
1	*"A major problem is there are certain risks you need to capture and it's very hard to filter out things that are likely to be false positives"*
2	*"The volume of false positives. Industry-standard, I think, is slightly improving now, it's about 90 to 95%"*
3	*"Every risk you pick up means an alert and investigation. This has a huge cost on the investigation side, operational cost basically"*
4	*"We are constantly trying to keep down on backlogs and false positives, so focusing on new and emerging risks doesn't become the focal point"*
5	*"It's very hard for companies to get a good understanding of how effective or efficient their monitoring solution is"*
6	*"The major challenge in banks and transaction monitoring systems is actually keeping up with new types of crimes"*
7	*"So currently because we're producing many events for the rule-based system, it means we need to ask our customers many questions. So that creates a huge amount of customer dissatisfaction"*
8	*"Customer segmentation is a very clumsy, very 1990s technology because the first of these monitoring engines were built around the early 2000s, so they're reliant on that 1990s view of the world, and it still haunts us today"*
9	*"Having to spend a lot of money on constantly refreshing your segmentation, constantly re-tuning, constantly testing that your thresholds are accurately set, checking you're below the line testing and wide open testing to see whether you're missing things that you should be picking up erodes the accuracy of the traditional rule-based method you're setting up"*
10	*"It is challenging to monitor dual-use goods transactions. They are called duel goods as you can buy metal for good purposes but you can also use metal to make arms"*

additional components, are still widely used, several institutions are considering or beginning to transition to machine learning techniques for AML activities [38].

4.2. Challenges in transaction monitoring

This section identifies the problems and challenges that financial institutions encounter in transaction monitoring. Table 3 concentrates on challenges concerning the current transaction monitoring methods utilised in the industry. Crucial issues such as high volumes of false positives, being ineffective and slow, struggling to identify new risks, and being costly are highlighted by experts. Institutional challenges affecting transaction monitoring are presented in Table 4. Some challenges include, AML departments working in isolation, loss of valuable information in investigations, poor data quality and accuracy, and the difficulty of transitioning to machine learning from rules-based approaches are stated.

4.2.1. Challenges of the current methods

The findings show that one key problem in transaction monitoring that was repeatedly mentioned is the high number of false positives that are generated. It is difficult to filter out false positives from large volumes of transactions, especially when certain risks need to be captured. The industry average for false positives, which has been improving in recent years, was mentioned to be around 90%–95%, in line with the current literature [39].

A high false positive rate leads to multiple issues in banks and is a major problem that has to be addressed to enhance detection. It negatively impacts the institution by increasing operational costs and the number of resources required to investigate alerts. As institutions need to investigate every alert the more false positives lead to more employees analysing alerts.

Another challenge that arises due to spending large amounts of resources on backlogs and false positives is the lack of ability and time to focus on new emerging risks. This will cause problems in the future as banks will not be able to adapt to criminals evolving techniques and fail to detect fraudulent transactions. The issue of false positive alerts also impacts customer experience, as these alerts often result in additional information required from customers. This can negatively impact customer satisfaction, particularly when the alert is a false positive. An additional problem that causes customer dissatisfaction is during the production of rules, events, and scenarios for the current rule-based methods, which can result in losing customers.

Identifying the effectiveness and efficiency of the current transaction monitoring methods is another challenge within financial institutions. It is crucial to understand how and what your transaction monitoring model covers to develop and enhance it. Uncertainty regarding the type of risks the institution covers and lack of clarity can be very problematic and costly to institutions considering the high standards regulators set. The rules-based methods' slow speed at processing transactions is also identified as a problem. Slow processing time can impede efficiency and effectiveness in identifying potential risks, which can result in a regulatory cost for banks. Another issue with current rules-based methods that can cause problems with regulators is the ability to keep up with new and emerging types of money laundering and terrorist financing, which is also mentioned in the literature [6]. The inability of rule-based models to adapt to changes in customers' behaviour is an additional weakness, as a larger number of false positives can be generated. To compound this problem, maintaining the rules and performing effective testing is complex and costly for institutions. Also, the difficulty of motioning duel use goods was found during this study as well as cross-bored transactions, which is also stated in the current literature [40]. It is challenging to distinguish between using duel-use goods for legitimate reasons or potentially dangerous ones.

The findings from the semi-structured interviews indicate that certain specialists view customer segmentation and threshold setting within traditional rule-based monitoring methods as outdated and cumbersome, failing to accurately capture customer behaviour. Customer segmentation is seen as a 1990s type of technology and an old way of thinking that negatively impacts the transaction monitoring domain today. The complex nature of customers' behaviours, and the challenge of accurately segmenting customers, further complicates the issue. Therefore, these challenges result in a high rate of false positives, an inaccurate view of customers' behaviours, and higher costs for re-tuning and testing.

4.2.2. Challenges within the institutions

Various departments in financial institutions have significant indirect impacts on the transaction monitoring process. One major issue is that Know Your Customer (KYC) information is often outdated and inaccurate, leading to either over-alerting or under-alerting on particular individuals. This negatively impacts the customer segmentation process and reduces the accuracy of the overall process. Additionally, the departments in AML (i.e. KYC) need to be embedded within the transaction monitoring and work together, not in isolation. Working in cohesion will greatly impact the accuracy and efficiency of the entire AML process. Another issue raised by a specialist is that organisations have to be cautious of the resources and expertise that are given to upstream processes, as it has a positive impact on downstream processes like transaction monitoring. The investigation process in AML also needs improvement as there is often not enough information on why an alert is closed, which limits the ability to learn from these cases by a feedback loop.

Data is a challenge in institutions and there is a need for a "golden source" of internal data that provides a single customer source with accurate and up-to-date information about the customer. The fact banks often have multiple sources of data from various departments and products adds to the single data source issue. The interviewees also highlight the impact of data quality and inaccuracy on transaction monitoring, with discrepancies between different customers' data, due to evolving regulators, creating problems for rule-based methods. Onboarding customers in the past differentiates from now and if the data is not updated regularly problems occur. Many AML experts included

Table 4
Quotes on the problems and challenges within the institutions affecting transaction monitoring.

	What are the problems and challenges within the institutions affecting transaction monitoring?
1	*"What we're lacking today is that KYC doesn't get updated as often, so unfortunately what happens is you over-alert or you under-alert on some people"*
2	*"KYC needs to be embedded within your transaction monitoring solution and your sanctions. However, controls are currently working in isolation but should be more aligned. So as an example for KYC, we can get them to ask questions from a transaction monitoring perspective"*
3	*"Currently you have a drop-down list of five reasons why you closed the alert, you can't really learn anything from that"*
4	*"Making sure to have a golden source for internal data, is one of the main challenges today"*
5	*"If there was an all-in-one data source then multiple data sources wouldn't be a problem"*
6	*"There's a lot of rules and scenarios which have to run on bad quality data, which is either out of date or not detailed enough"*
7	*"If you're monitoring across 58 countries like we are, not all of those countries allow data sharing between jurisdictions, so you have to set up different models in different jurisdictions. All financial institutions suffer the same"*
8	*"A big pain point is to understand how you can move from rule-based to AI. That's probably a little bit of the solution to the productivity issue too"*
9	*"A lot of the things that we're doing are reactive rather than proactive, so we're not necessarily harnessing the data and understanding where it starts to change"*

in this study highlighted the data quality issue impacting transaction monitoring. Incomplete data sets and data complexity present challenges to transaction monitoring, especially in the context of building new models. Many research articles in the literature have mentioned data issues in transaction monitoring [7]. Finally, the interviews indicate that monitoring customers across multiple jurisdictions presents data challenges, as not all countries allow data sharing. Data privacy was also identified in the literature as a problem [41], as it forces institutions to set up different models in different jurisdictions.

Another challenge in institutions is understanding how to move away from the current rules-based methods and implement new solutions. The transition away from current systems will be complex and time-consuming, therefore, institutions need to bring in specialists with the necessary knowledge and skills to transition smoothly. Furthermore, the current approach in the AML departments tends to be reactive whereas banks need to be more proactive in detecting and addressing potential risks to start making a change.

4.3. Requirements

This section presents the features and capabilities that are required by a new transaction monitoring method, found during this study, to produce efficient results and be successfully deployed in the industry. The requirement features are then analysed and discussed. Table 5 presents the quotes from the interviewees on the requirements for a new transaction monitoring method. Additionally, an importance score given by the specialists for various features, along with an average rating for each feature, is presented in Table 6. Each feature is described as follows:

- Explainability — the method's ability to be able to explain or interpret why it has flagged a transaction as suspicious;
- Flexibility — the method's ability to adapt to changes in customers' behaviours over long periods;
- Detection speed — how quick the method can identify the suspicious activity from when it took place;
- Scalability — the number of transactions that can be processed by the new approach;
- Customer experience — how important the customer experience is in transaction monitoring.

Table 5
Quotes on the requirements for a new transaction monitoring method.

	What is required from a new transaction monitoring to be successful in the industry?
1	*"Explainability of the method is key because if there are any regulatory or audit issues, you've got to be able to explain your method"*
2	*"I think the main problem is that regulators are not convinced with it (artificial intelligence). So you really need to be able to know what you're building, why you're building it, what your objectives are, what your risks are, and how you can explain it as well"*
3	*"If the method can't adapt properly you will get a whole bunch of false positives due to seasonality or changes of behaviour"*
4	*"Transactions are only relevant in the context of other transactions, so you might have scenarios that work based on looking at three months' worth of transactions and then seeing how they relate to each other. Detection speed is important, but you may not always pick up your scenarios. A transaction tool may see three transactions that are similar and then the third aggregates all three and reports that"*
5	*"Banks process millions of transactions every day. So when running a detection capability across a large bank everything has to be scalable"*
6	*"As we are producing a lot of events for the rule-based system, it means we need to ask our customers a lot of questions. So that creates a huge amount of customer dissatisfaction"*
7	*"When the transaction gets flagged and goes into the investigation stage, we learn a lot of information, you can reuse that information intelligence to improve detection"*
8	*"I'm a part of a regulatory group on monitoring, and in the recent meeting we had, it was clear that institutions are still struggling with the accuracy of monitoring"*
9	*"I think it's going to be quite critical to identify any new risk that we can't think of. Can we get machines to identify unusual behaviours in the data compared to its peers or a group of people, and show new risk"*
10	*"To be able to successfully implement a new method you need to consider the resources required, how can an effective team size manage it? Implementation experience of that team?"*

4.3.1. Explainability and effectiveness

Explainability and effectiveness were identified as a requirement for a new transaction monitoring method by multiple specialists during the semi-structured interviews. An average importance score of 9.1 was given for explainability showing the value it has in the transaction monitoring domain. Explainability is crucial to satisfy regulatory and audit requirements is any issues arise. The importance of transparency in methods for transaction monitoring was further stressed as institutions need to explain how it works and the risks they are covering to regulators. Therefore, the explainability of the method is crucial and can be achieved by understanding what it does, why it was built, and how it works. Along with the explainability of how the method detects transactions, showing the method's effectiveness is equally as important. Overall, explaining how the method reaches its outcomes and proving effectiveness are crucial requirements for a new transaction monitoring method [5].

4.3.2. Flexibility

During the interviews, the specialists highlighted the value and necessity of flexibility in a new transaction monitoring method and gave an average importance score of 7.6. Adapting to unforeseen circumstances can lead to a more stable model that consistently achieves greater accuracy. Having a flexible method will also reduce the number of false positives during seasonality or periods when customers' behaviours are changing [42]. Flexibility will give an institution the ability to customise the detection process and adapt to future changes in transactions and regulations.

4.3.3. Detection speed

The AML specialists involved in this study gave an average importance score of 5.5 for detection speed for a new transaction monitoring method. The findings show that participants agreed that while detection speed is important, it is not always the most critical factor [43]. In transaction monitoring to detect a suspicious customer sometimes

Table 6
Importance of features given by specialists for transaction monitoring methods in AML.

Question: On a scale of 1-10, how important are the features listed below for a transaction monitoring method in AML and why?

Features	Specialist								Average score
	1	2	3	4	5	6	7	8	
Explainability	9	9	8	10	10	8	9	10	9.1
Flexibility	8	10	7	7	9	5	8	8	7.6
Detection Speed	7	5	5	5	6	2	8	7	5.5
Scalability	10	9	8	8	9	5	7	10	8.2
Customer experience	9	1	4	4	1	1	9	1	2.6

you need to look at the customer's transactions over a long period to identify if their patterns are suspicious. Transactions are linked and related to each other, therefore, context is required before alerting a report which can take an extended period of time reducing detection speed. The finding indicates the importance of taking the time to analyse transactions and the need for a balance between speed and accuracy for a new transaction monitoring method. While regulators value quick detection speed, they understand that transaction monitoring is a complex process. Ultimately, the main purpose is to accurately identify and stop the maximum amount of money launderers.

4.3.4. Scalability

The requirement of scalability for a new transaction monitoring method is evident from the quotes of the interviewees and the importance rating given by the experts. Financial institutions are required to process millions of transactions daily. The findings demonstrate that scalability is crucial for a new transaction monitoring method to handle the amount of data produced daily. Additionally, an average important score of 8.2, reinforces the significance and need for scalability. A scalable method will make it possible to deploy the approach in the industry and enable the identification of suspicious activities in large datasets [17].

4.3.5. Customer experience

Mixed responses were given on how transaction monitoring affects the customer experience. This was due to various institutions having different approaches and processes for transaction monitoring. A majority of the specialists did not regard the customer experience as very crucial, as the AML process did not impact the customers. The customer only gets affected post transaction monitoring, specifically during the investigational stage. However, some institutions contact customers and ask questions during or before the transaction monitoring process to create accurate events and rules, which can cause dissatisfaction. An average importance rating of 2.6 was given for customer experience with a large range due to the differences in financial institutions.

4.3.6. Feedback loop

AML specialists stressed the importance of reusing investigation outputs through a feedback loop as it is the best source of additional data. This finding highlights the potential use of data obtained during the investigation stage to continually improve the detection accuracy in transaction monitoring methods [44]. This approach can reduce false positives drastically and provide individual customer-level monitoring that can adapt to specific customers' behaviours. Financial institutions hold a lot of intelligence that should be used to enhance transaction monitoring further and more research is required in this field.

4.3.7. Higher accuracy

There is a need for higher accuracy in current transaction monitoring approaches, due to the high occurrence of false positives and a lack of efficiency [45]. The requirement of attaining a higher accuracy for a new approach was crucial for the specialists. The findings suggest that the AML sector is seeking to attain greater accuracy for detection. An interviewee in the financial sector and a regulatory group stated emphasised the challenges around detection in the AML field. These results highlight the limitations of traditional methods and the need for advanced machine learning models.

4.3.8. Identification of new risks

The AML specialists highlighted the importance of identifying any new risks that can emerge in transactions. Along with identifying new risks, the importance of identifying hidden relationships was mentioned. Meeting this requirement would not only improve the productivity of transaction monitoring methods but also ensure compliance with regulatory requirements, preventing potential fines, and damage to reputation [46]. However, keeping up with the ever-changing landscape of criminals' complex money laundering techniques is very challenging and costly.

4.3.9. Efficient customer segmentation

Some specialists included in this study consider an efficient customer segmentation process as a requirement for a new transaction monitoring method. They emphasise that a precise and efficient customer segmentation process can enhance the accuracy of detecting money launderers in several ways. Customers can be monitored based on tailored risk profiles and their different behavioural patterns. Despite specialists' scepticism towards clustering customers, they recognised the significance of customer segmentation if done right.

4.3.10. Implementation

The understanding of implementation was identified as a requirement for a new transaction monitoring method. The findings highlighted the importance of considering how a new method can fit and be implemented into an institution and recognise the numerous challenges that can arise during the integration process into existing systems and processes [22]. Although developing an effective transaction monitoring method is crucial, having a well-equipped team with the right skills and experience to manage the implementation process is equally important.

4.3.11. Handling seasonality

During the semi-structure interviews, the specialists emphasised the need for a new method to account for seasonality. During months or times when unexpected activity is going to take place, it should be able to handle it, learn from previous situations, and not produce a huge amount of false positives. However, the new method must still be able to detect suspicious behaviour within the context of expected patterns. Overall, to enhance efficiency and reduce the occurrence of false positive alerts the new method should be able to adjust to seasonality while identifying suspicious activity.

4.4. Artificial intelligence and machine learning for transaction monitoring

When AML specialists were asked about the role of artificial intelligence and machine learning in the field of transaction monitoring it was clear that the interviewees believed the domain was heading towards adopting these technologies. The findings of this research are in line with the current literature, as proven by the number of articles released on machine learning for transaction monitoring in recent years [5]. Table 7 shows the quotes from the interviewees about their opinions on using artificial intelligence and machine learning for transaction monitoring.

Table 7
Quotes from the interviewees on their opinions on Artificial Intelligence and machine learning for transaction monitoring.

	What are your opinions on artificial intelligence (AI) and machine learning for transaction monitoring?
1	*"I think AI and machine learning is the only way forward for us"*
2	*"AI is now an absolutely key part. If you get your AI right, then everything else under that will be far easier to manage"*
3	*"I think at the moment we're in a transition stage from very rigid, strict, mature rules-based systems and now moving towards a more analytical platform with advanced capabilities such as entity resolution, machine learning, and graph analytics"*
4	*"Problems relate a lot to the rules-based solutions versus AI and I think banks are behind with AI generally"*
5	*"I think it needs to be a bit clearer on what the industry means by AI and machine learning and how it can be applied because it has been thrown around for quite some time without much change in the industry. How can AI be used and harnessed? I'm a bit sceptical of it"*
6	*"I think being able to tell, just with the transaction data (using machine learning) is a long way off for the industry"*

The specialists stated that artificial intelligence is the way forward and will make processes under transaction monitoring easier to manage. Machine learning techniques can better handle the complexities of detecting money launderers and can update systems quicker and more efficiently than current rules-based methods [21]. The study implies that a transition is underway in transaction monitoring, moving from strict and rigid rules-based systems towards more advanced capabilities. These include entity resolution, machine learning, or graph analytics. However, banks are lagging in the adoption of these technologies. Issues such as not having the necessary infrastructure and shortage of skilled and knowledgeable staff in the machine learning field to facilitate and manage systems prevent financial institutions to implement artificial intelligent lead solutions. Overall, the specialists are optimistic about machine learning solutions, but further work is needed to fully leverage the potential of these technologies.

One specialist expressed some scepticism towards the implementation and use of machine learning in the transaction monitoring domain. The expert highlighted the need for greater clarity of artificial intelligence implications for the industry as it has been a discussed topic for an extended period of time without substantial change. They believed that detecting money launderers just through transactional data is "a long way off" for many banks. Although this particular interviewee gave diverging viewpoints compared to the other expert's opinions they recognised the relevance and potential of machine learning in this domain.

4.5. Future of the domain

During the interviews, AML specialists discussed their perspectives on the future of the transaction monitoring domain. Table 8 presents thematic analysis results on the future of the transaction monitoring domain. It was believed that in the future regulators may expect enhanced transaction monitoring capabilities and can question institutions that have not adopted or incorporated them.

Institutions with access to technology, data, and skilled personnel will be required to develop artificial intelligence or machine learning solutions. Another interviewee noted that, in the future, regulators are likely to expect the implementation of machine learning. It was highlighted that, despite initial hesitations towards automated transaction monitoring, the same regulators mandated its use by major banks within five years [6]. This insight implies that machine learning is likely to be used for transaction monitoring in the future, which agrees with the existing literature, although regulators are currently sceptical. Therefore, it may be crucial for financial institutions to adopt machine learning as early as possible to prevent potential problems down the line. In the future, once machine learning and artificial intelligence are adopted by financial institutions, one specialist believed that transaction monitoring will be used to predict criminals and prevent their actions before the crime takes place. Overall, its thought that machine learning will be a key component in transaction monitoring and evolve the domain further.

Table 8
Quotes of interviewees on the future of the transaction monitoring domain.

	Where do you see the future of the transaction monitoring domain heading?
1	*"In three years' time, regulators can say you had the technology, data, and the people with the capability and skills to develop all of this, but you didn't build an artificial intelligence or machine learning lead method. Why not?"*
2	*"In the past, regulators were a bit nervous about automated transaction monitoring which is currently used, but within five years the same regulators were telling its major banks they had to use automated transaction monitoring capabilities for customer monitoring. If they weren't then they needed to be able to explain why. I think in five years' time we'll have the same regulators, who are nervous about machine learning capabilities now but will be expecting it in the future"*
3	*"The expectation will be that we don't retrospectively look at what has happened. Instead, we use the technology we have to look forward. We will say we think this presents a risk we are not willing to take, even if we don't have any evidence to suggest it is a crime. However, there may be evidence to suggest it could become one in the future. This is the direction technology is taking us, whether we like it or not."*
4	*"A regulator looking backward will say, you developed machine learning capabilities that were capable of predictive behaviour and predictive modelling. You had the capability of the people and the analysts in your bank to do that and you didn't use it to predict that this particular subset of customers were terrorists. Then you have done something bad and it can have problems with the regulators"*

Table 9
Quotes of interviewees on the type of approach for producing new transaction monitoring methods.

	What type of approach can be used when producing a new transaction monitoring method?
1	*"There are smaller components that could be enhanced by machine learning first and foremost. The first way could be alert prioritisation, understanding where the biggest risks lie so that more attention and focus can be prioritised on that area"*
2	*"Using machine learning to hibernate alerts to detect and tell us you're probably going to close this alert without raising a suspicious activity reports (SAR) so we shouldn't actually investigate it any further"*
3	*"Currently a lot of tricky rules are trying to identify hidden relationships. So how could you use entity resolution and work out what the key links between different parties or different sorts of companies are, to allow you to do advanced hidden relationship identification? That leads to graph analytics. So focusing on patterns rather than transactions, to find hidden networks and relationships"*
4	*"Look at what is normal and then at the things that are outside of that? Next use outlier analysis and aggregation to create a risk view of a particular customer and then based on that aggregation of risk, you can decide whether to look at them through an investigation or not"*
5	*"With scorecards, you get interested in a transaction because of risk. Then you look at other factors and risks of the transaction, giving it a score, and if it adds up to a certain score you decide to flag it"*

4.6. Transaction monitoring approaches

This section outlines and explores the transaction monitoring method identified by AML specialists during the interviews. It discusses different approaches that can improve the current transaction monitoring methods. One specialist suggested utilising machine learning as an add-on tool for current rules-based methods to hibernate alerts. Other methods such as anomaly detection and graph machine learning were also suggested. Additionally, a scorecard approach to prevent money laundering was proposed. Table 9 presents the key quotes from the interviews.

An approach suggested by multiple specialists is to incorporate machine learning as an add-on tool to the current rules-based methods. The experts offered valuable insights into the potential use of machine learning as a hibernation or alert prioritisation model. Alert prioritisation can provide institutions with a deeper understanding of high-risk areas allowing for more attention and resources to be allocated accordingly. Additionally, it can be an easy way to initiate machine learning adoption in institutions, while being a cost-effective and easily implementable approach. A risk migrating and alert hibernation approach were also proposed to reduce the number of false positives and the number of redundant investigations. Utilising historical suspicious activity reports and past experiences with unsuccessful alerts, machine learning can recommend, with a degree of confidence, whether to investigate a specific transaction. In the current literature, several researchers have proposed alert prioritisation and hibernation methods for transaction monitoring [47]. Although these approaches benefit institutions in multiple ways, they may not be sustainable in the long term, as it builds upon an existing, potentially inefficient method.

Graph analysis approach was identified by the specialists as a potential transaction monitoring method. An interviewee quotes highlights the need to move away from traditional rules-based detection and towards a more advanced approach that leverages graph analytics to identify hidden relationships. It is believed graph analysis should focus on patterns instead of individual transactions to identify hidden networks and relationships. Graph machine learning constitutes a scalable methodology capable of handling large volumes of data while conducting holistic analysis which can address the high false positive issues creating an efficient approach. Overall, the specialists acknowledge the value of utilising graph analysis for monitoring but understand the difficulty of successfully achieving such an approach. Challenges such as the complex routing of money through entities and other financial markets by criminals make it difficult to identify hidden relationships. While the application of graph machine learning has been explored in the current literature, further research is required for advancements [5].

AML specialists identified anomaly detection using machine learning as another approach to enhance transaction monitoring. Improvements in detecting money laundering can be achieved by training a machine learning model with a dataset of 'normal transactions'. This model can then identify and flag any transactions that diverge from these established norms as potentially suspicious. Given the vast amount of transactions that are deemed "normal" in financial institutions, an anomaly detection approach can yield promising results, however, it can be computationally expensive. An anomaly detection and data-driven method is thought to be able to increase the accuracy and reduce the amount of false positives compared to the existing methods in the industry. The "normal transactions" dataset must be large and of high quality to attain desirable and accurate results, otherwise, fraudulent transactions can process undetected. An autoencoder technique [48] is published in the literature with a similar methodology along with many other anomaly detections approaches for transaction monitoring [21].

During the semi-structured interviews specialists stated that they were exploring and working on a scorecard model for transaction monitoring. They believed that a scorecard model would allow for a more holistic monitoring of transactions and consider multiple factors and risks of the transactions before making a decision. A specific set of rules or scenarios with different weights based on risk is required to build a scorecard approach. For each rule, a transaction triggers an individual score is given. Subsequently, these scores are aggregated to determine if the transaction should be alerted. A benefit of the scorecard method is that it allows the institution to control and reduce the volume of false positives produced. This method could improve current transaction monitoring methods, however, it would be very difficult to set accurate weights for the rules, which could lead to low accuracy. The scorecard approach could be explored further as there is limited research in the existing literature due to most efforts focusing on machine learning solutions.

5. Conclusion

In conclusion, this study explored the current transaction monitoring approaches employed in the industry, as well as the challenges associated with them. Furthermore, the research delved into artificial intelligence and machine learning in transaction monitoring, analysing the specialists' opinions and the future of the domain. In addition, requirements for new solutions are presented along with specialists' opinions on potential future transaction monitoring approaches.

The findings of this research suggest that the current transaction monitoring methods are inefficient and highlight the problems it brings to institutions such as high false positive alerts, low detection accuracy, and increased operational costs. A transition from strict, rules-based methods to more advanced machine learning capabilities is seen to be taking place and believed to be the solution for the future of the domain. Although there is optimism surrounding advanced capabilities, it is crucial to acknowledge that additional work and research are required to adopt these technologies.

To specifically address the significant challenge of high false positive rates in transaction monitoring, the study highlights potential solutions. Utilising and experimenting with advanced machine learning models, such as graph machine learning or the transformer architecture, could reduce false positives, as these methods' ability to identify and distinguish complex patterns surpasses rule-based approaches. Additionally, analysing transactions at multiple levels could offer a more comprehensive examination, reducing false positives. This study identified that focusing solely on individual transactions may be insufficient, so expanding the analysis to include group and individual customer-level transactions could enhance efficiency and detect both global and local patterns. Incorporating a feedback loop into the system could continuously refine its precision, allowing it to learn from past true and false positive alerts and, over time, better understand each client's behaviours, reducing false alerts. The utilisation of high-quality datasets is fundamental to any solution to ensure reliability. However, the findings indicate that attaining such a dataset can be challenging due to multiple data sources and missing information, suggesting that adequate time and resources should be allocated to collect a high-level dataset.

Analysing the semi-structured interviews provided requirements for a new transaction monitoring method to be successful and efficient, emphasising the need for scalability, high accuracy, proving effectiveness, regulatory compliance, and explainability. Desirable features such as information feedback loops, flexibility in customers' behaviours, and the ability to identify hidden relationships were also identified. Various approaches to enhance transaction monitoring suggested by the specialists were also explored, including add-on tools to current rules-based methods, graph analysis, and anomaly detection techniques. Additionally, a scorecard method was identified and discussed during the interviews.

This study contributes to the existing literature on transaction monitoring and anti-money laundering by conducting semi-structured interviews with specialists in the domain. Excessive analysis of experts' opinions and knowledge provides a deeper insight into the current problems and requirements for new solutions in transaction monitoring. Currently, in the literature there is a disconnect and lack of studies between industries and academicians around transaction monitoring, this study bridges the gap to gather a better understanding of what is expected and required. These findings can assist researchers and stakeholders to get an in-depth understanding of the problems in the transaction monitoring domain and provide a guideline to produce successful and efficient transaction monitoring methods to meet the industry's requirements.

In summary, improvements are required in the transaction monitoring domain to detect money laundering activities with higher accuracy and efficiency. It is crucial for researchers to continue investigating solutions with advanced capabilities. Although there are challenges to overcome and further research is needed, the AML specialists' perspectives and opinions suggest that technologies such as machine learning will greatly enhance the field. Adopting artificial intelligence and machine learning will not only improve the detection of money launderers but also pave the way for more innovative and enhanced approaches that can address the ever-changing challenges in the anti-money laundering industry.

CRediT authorship contribution statement

Berkan Oztas: Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Conceptualization, Methodology. **Deniz Cetinkaya:** Validation, Writing – review & editing, Supervision, Conceptualization, Visualization. **Festus Adedoyin:** Validation, Writing – review & editing, Supervision, Conceptualization. **Marcin Budka:** Validation, Writing – review & editing, Supervision, Conceptualization. **Gokhan Aksu:** Validation, Writing – review & editing. **Huseyin Dogan:** Validation, Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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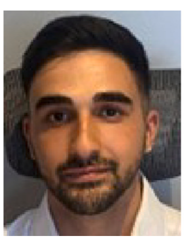

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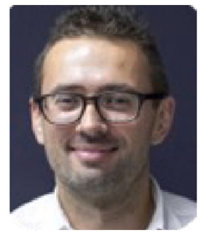

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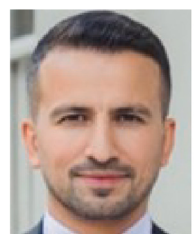

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