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Fraud Detection and AML Analytics in Real-Time Payment Systems

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Abstract- They've opened up the door to instant fund transfers and around-the-clock availability. But at the same time made us more exposed to scammers and money laundering schemes, when real-time payments became a norm. Coming racing up against the tight timeframes and limited space to go back and correct anything that's gone wrong, the old way of doing things just isn't working anymore. This paper takes a hard look at the analytical and infrastructure-related issues surrounding the detection of fraud and money laundering in real-time payment systems, where speed, accuracy and meeting regulations all need to be juggled at the same time. Well-known techniques won't cut it anymore in the world of real-time, so the researchers here take a more applied approach, merging real-time analytics systems, cutting-edge fraud detection and money laundering models. They lay out a comprehensive blueprint for real-time transaction analysis, fine-tuning features for ultra-fast decision-making, hybrid rule-based and AI-driven systems and risk-scoring that's tailored to the flow of instant payments. When evaluating the performance of fraud and money laundering systems in real-time, this paper looks beyond the traditional measure of accuracy and zeroes in on things like response times, scalability and false positives, which are pretty critical in the real-time world. The real contributions of this work are threefold: a crystal-clear picture of the threats facing real-time payments, a logical analytical framework that gets the balance between detection models, real-world timeframes and regulatory expectations, and some down-to-earth advice on how to run your fraud and money laundering systems in a way that is not only effective but also explainable and scalable.

Keywords – Real-Time Payments, Fraud Detection, Anti–Money Laundering (AML), Financial Analytics, Machine Learning.

I. INTRODUCTION

They shook up the way financial transactions go down around the world, when real-time payment systems began to take off. Coming running over straight from the source, instant settlement, 24/7 operation and irreversible transfers have made things a lot easier for both individuals and businesses, but they've also exposed us to some nasty fraud and anti-money laundering problems. Well-known scammers are using the short turnaround times and reduced opportunity for post-transaction checks to their advantage, and as real-time payments are spreading to more countries, it's becoming increasingly clear that the current methods of managing risk aren't going to cut it anymore. Real-time payments throw up different types of fraud and money laundering than traditional payment systems, and the need for real-time authorisation and settlement limits the time financial institutions have to dig into the details of a transaction. For the rapidly growing world of instant payments, new and evolving frauds, such as push payment scams and money laundering networks, pose an existential threat to the integrity of these systems. These kinds of frauds require fraud detection mechanisms that can be accurate, super-efficient, and able to operate within a 1-millisecond window. However, conventional transaction monitoring methods, heavily reliant on batch processing, static rules and retrospective analysis, are poorly aligned with the high-speed and instant nature of real-time payments.

These methods frequently generate alerts after the funds have been transferred, resulting in delayed intervention and a spate of elevated false positive rates, a crippling strain on the system, and a degradation of customer experience. As the need for high-speed fraud detection continues to mount, we are required by the hour to create analytics-led answers to this challenge. Well-known transaction monitoring frameworks won't do the job. The current approaches which use batch processing, static rules and looking back in time won't work well for real-time payments. This paper delves into the issue of fraud detection and AML analytics in the context of real-time payment systems. Its main goals are to outline the nature of real-time fraud and money laundering, propose a merged analytics and system architecture that's particularly made for instant payments, and see how well it works. Coming from here, we'll cover the related literature, the particular risks associated with real-time payments, our proposed system structure, analytical models

and way of measuring performance, regulations and governance considerations, and a wrap-up of the challenges, future areas of study, and last thoughts.

II. RELATED WORK

In the case of financial fraud detection, the field has been extensively studied over the past few decades, with researchers trying to stay one step ahead of the fraudsters. In the past, fraud detection systems were based on fairly rigid and static rules and monitoring, where pre-defined conditions triggered alerts for suspicious transactions. Although this kind of system provided a basic level of security, it often failed in its task. It was found that fraudulent transactions continued to be found in the system with alarming frequency, so a brand new direction in fraud detection has appeared, relying on large-scale data analysis and machine learning. Using a combination of historical transaction data, behavioral patterns and surroundings to identify odd behavior that may be indicative of fraudulent activities, this kind of system has proven to be very effective in the field, with the work of Baesens et al. In 2021 and Bi et al. In 2019 being particularly influential. Supervised learning techniques such as decision trees, support vector machines and gradient boosting have demonstrated their ability to classify legitimate and fraudulent transactions, with the strength of unsupervised and semi-supervised systems in picking up brand-new types of fraud being a significant bonus.

Anti-money laundering or AML analytics has become a high-priority area of financial regulation and risk management, and traditional methods of AML don't hold up too well in the face of increasingly complex money laundering schemes. Regularly, conventional AML systems are run on transaction tracking and consumer profiling to spot suspicious behavior, relying on regulations such as suspicious activity reports (SARs) and the importance of "know your customer" (KYC). They're based on rule-based calculations, things like limits on transaction amounts, speed of transactions, and patterns that trigger alarms for possibly shady behavior, but these have trouble getting past the most sophisticated money laundering schemes, including those that use layering, structuring, and networked transactions.

Well-known techniques in recent years have been using graphs, network analysis and machine learning to lift the veil on these intricate money laundering patterns and are showing off improvements in accuracy and the ability to map out connections between various entities. Blending rule-based logic with predictive models is also an area of interest, allowing financial institutions to catch both known and novel risks, and make sure they are in line with regulations. Concerning fraud detection and anti-money laundering in the financial sector, the majority of existing methods are outdated. They were initially designed for batch processing and periodic reviews, and with the rise of instant payments and continuous settlement, these methods are unable to keep up. Rule-based systems may be slow and rigid in real-time payment processing, and most machine learning models were trained on historical data and don't account for the time-critical nature of payments.

The dynamic and evolving nature of fraud and money laundering in real-time, also exposes weaknesses in the adaptability of models, data ingestion pipelines, and system scaling, several studies, one of them by Baesens et al. In 2021 show the need for something that can instantly update our understanding of fraud and send out warnings. This is where streaming analytics and adaptive learning fit into the picture, but are still very much in their infancy. Coming from a different angle, a critical challenge exists in turning traditional fraud detection and money laundering systems into something that can operate at the speeds and volumes seen in high-stakes payment systems.

Another pressing problem, regulation in real time, presents many challenges, where the financial system has to not just accurately identify suspicious transactions, but also ensure that they're transparent, audit-able, and in harmony with things like the AML directives and data protection laws, as found in the study by Bertrand et al. Back in '21. If these compliance considerations are not carefully woven into real-time analysis, it may fall short in picking out the bad guys or send way too many false alarms which cripple normal payments, and so, calls for a complete solution that unites predictive analytics, infrastructure-level planning and top-level oversight. Well-known research has provided a strong basis for fraud detection and money laundering analysis, and shown the effectiveness of rules-based systems, artificial intelligence and network analysis techniques, but there's still lots of work to be done to make these methods work in real-time payment systems. Shortfalls in latency-optimised modelling, adaptive learning for ever-changing fraud patterns and linking up with operational and regulatory systems mean that the financial sector is not yet able to process instantaneous payments securely and in accordance with the rules.

III. FRAUD AND AML RISK CHARACTERISTICS IN REAL-TIME PAYMENTS

Examining real-time payments, fraud and anti-money laundering are the top concerns, thanks to the instant settlement and non-stop processing that these systems provide, and these aren't the same as the traditional batch-based transactions we're used to. Coming fast onto the heels of every single transaction, scammers can use the speed and irreversibility of these systems to their advantage, and before anyone can even intervene, as was also pointed out by Gao and Ye back in '07, and Ghosh and Reilly in '94. Well-known types of fraud in real-time payments include authorised push payment fraud, account takeovers, transaction laundering and synthetic identities, all of which rely

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on the rapid settlement to get past security measures, as Burdick et al. Explained in '14 and Graves et al. Confirmed in '21. Since real-time payments come from numerous financial institutions and mobile apps, the attack surface is massive and extremely hard to monitor. The same challenges apply to anti-money laundering, because it's almost impossible to keep an eye on all the transactions as they're happening, especially in real-time systems. Old-fashioned back-and-forth methods won't work anymore because the money moves too quickly. Once the money has gone, you're left with nothing. Criminals use techniques such as layering and cross-border structuring to throw investigators off the scent. We need to be able to spot unusual patterns in near real-time, and look beyond just transactional analysis to the personality-based patterns that could be a tell-tale sign of fraud. This was suggested by Bzdok et al. Back in '17.

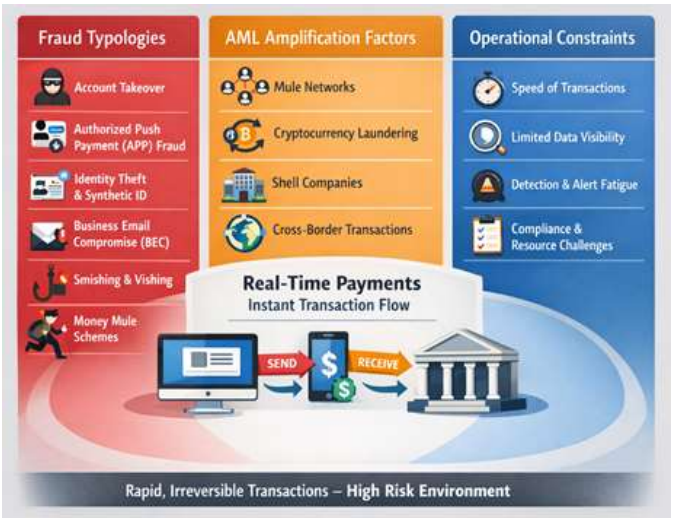

Figure 1: Fraud and AML risks in real-time payment systems

IV. REAL-TIME ANALYTICS SYSTEM ARCHITECTURE

In the case of real-time fraud detection and anti-money laundering (AML) analytics, a well-designed system is required to process a high volume of transactions with minimal delay. The architecture starts by capturing transaction data from various sources such as mobile apps, online banking platforms, and point-of-sale terminals. This transaction data is immediately fed into a streaming processing layer, which applies the first step in fraud and AML detection, consisting of validation, normalization, and feature extraction. The purpose of preprocessing is to take out useless data, iron out irregularities and slice out the features that can help us better understand the behavior of the transactions. This concept has been covered in works such as Burdick et al. In '14 and Bzdok et al. In '17.

Following ingestion, the decision engines kick into high gear analyzing the transactions using what is called a hybrid detection framework, which throws together rule-based logic, supervised and unsupervised machine learning and anomaly detection to spot suspicious activity.

If it's able to confidently flag a transaction as suspicious, the engine shoots out a risk score, alert or instruction for immediate action, all of which depend on the level of confidence and pre-set operational limits. The decision-making algorithm's outputs are fed into the payment authorisation system, giving the platform the ability to accept, reject or temporarily hold a transaction on the basis of its real-time assessment of risk. The fusion of fraud and AML measures is done in a way that prevents any slowdown in the payment process, while upholding consumer satisfaction and regulatory compliance, as shown by Galeazzi et al. In '21 and Ghosh and Reilly in '94.

Table 1: summarizes the key components and functions of a real-time analytics architecture for fraud and AML detection

Component	Function / Description
Transaction Data Sources	Capture events from mobile, online, and POS channels
Streaming Ingestion Layer	Validates, normalizes, and enriches data in near real-time
Feature Engineering Module	Extracts behavioral, transactional, and contextual features
Decision Engines	Applies rule-based, supervised, and unsupervised models for risk scoring and alerts
Alert and Response Mechanism	Flags suspicious transactions and triggers automated or human review
Integration with Authorization	Enforces risk-based transaction approvals without disrupting settlement

Figure 2: Real-time fraud and AML analytics architecture

As for processing large volumes of financial transactions, modern architectures have the ability to instantly sort out anomalies and react with precision. Financial institutions can now build systems that effectively balance operational

efficiency, regulatory and risk management requirements, and with a framework that's based on the rapid ingestion of streaming data and adaptable decision engines, they can set up fraud and AML systems that are highly scalable, and can operate in real-time.

V. FRAUD DETECTION AND AML ANALYTICS MODELS

Regarding fraud detection and AML analytics in real-time payment systems, the key is in the architecture and fine-tuning of the analytics models. To turn raw transactions into something that can be used in real-time analytics, feature engineering is the way to go, and it can pick up on things like behavioral patterns, the location where the transaction is coming from, how quickly the transaction is being processed, and the history of the customer. Advanced analytics also uses streaming data to update the risk scores so that the models stay on top of brand-new patterns without slowing down or sacrificing accuracy, a concept that Burdick, et al. Wrote about in '14.

Fraud detection in real-time settings can use both supervised and unsupervised techniques, with supervised learning methods such as gradient boosting, random forests, and neural networks being trained on labelled data to categorize transactions as genuine or fraudulent. Unsupervised and semi-supervised techniques like clustering and anomaly detection are very useful in pinpointing brand-new types of scams that aren't in the training data, as per Ghosh and Reilly's 1994 paper and Graves et al. In '21. The goal is always to strike a balance between detection accuracy and how quickly the decision can be made, and with real-time transactions, you can't afford to wait.

For Anti-Money Laundering (AML) analysis, the approach is more than just checking individual transactions, it's about the relationships and networks of transactions, accounts, and individuals, something that graph-based modeling can show us, by hooking into hidden links between different parts of the financial system, as seen in Galeazzi et al. In '21 and Gao and Ye back in '07.

To stay in line with regulatory requirements and flag suspicious activity quickly, we use techniques that sum up a combination of oddities, such as unusual transactions, and individual customer behavior that don't add up, plus prior AML alerts, into a composite risk score that we can monitor almost in real time. Today, lots of financial institutions are combining rule-based systems with machine learning to nail down both the well-known and brand-new threats, and they're using ensemble methods to blend the results of multiple independent models, boosting the overall accuracy of the analysis.

Table 2: Fraud and AML analytics models used in real-time payment systems

Model Type	Technique	Key Features	Operational Objective
Supervised Learning	Random Forest, Gradient Boosting	Transaction history, velocity, location, device ID	Predict fraudulent transactions with high accuracy
Unsupervised Learning	Clustering, Anomaly Detection	Behavioral deviations, network interactions	Detect novel fraud patterns
AML Analytics	Graph-based modeling, Risk scoring	Account relationships, layering, structuring	Identify laundering schemes
Hybrid/Ensemble	Rule + ML, Voting/Stacking	Combined transaction rules and predictive scores	Optimize detection under real-time constraints

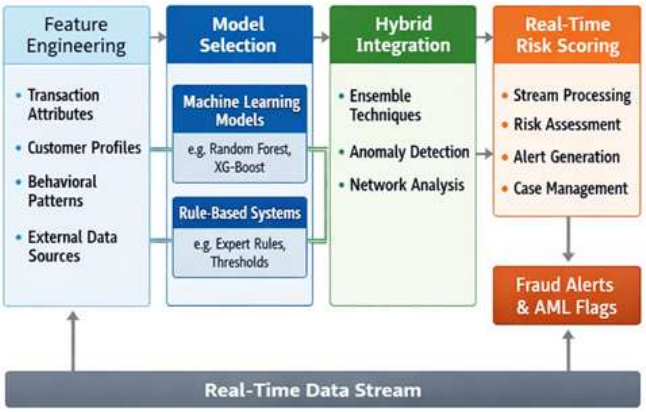

Figure 3: Real-time fraud and AML analytics framework

Concerning fraud detection and AML analytics in real-time payment systems, a well-rounded and systematic approach is required. Feature engineering is used to capture all the relevant transactional and behavioral signals, so that the fraud detection algorithm can be made aware of these patterns. Supervised, unsupervised and graph-based models are at the heart of the predictive capabilities, and using hybrid and ensemble approaches helps to make these predictions even more robust and adaptable. Combining all of these techniques, financial institutions are able to effectively detect, respond to and combat fraud and money laundering in real-time payment systems. A concept that was also highlighted by Burdick et al. In 2014, Bzdok et al. In 2017, Galeazzi et al. In 2021, Gao & Ye in 2007, Ghosh & Reilly in 1994, and Graves et al. In 2021.

VI. MODEL EVALUATION AND OPERATIONAL PERFORMANCE

When evaluating the performance of fraud detection and anti-money laundering (AML) analytics models in real-time payment systems, the impact of predictive accuracy is not the only consideration. The operational efficiency of the model must be weighed against the stringently short latency that real-time systems demand. Traditionally, metrics like precision, recall, F1-score and area under the receiver operating characteristic (ROC-AUC) play a major part in measuring the accuracy of classification, and allow us to see how well these models can tell the difference between legitimate and fraudulent transactions, a point made clear by Bzdok et al. In '17, and by Ghosh and Reilly back in '94. Precision looks at what percentage of the transactions that are flagged as suspicious are actually fraudulent, and recall measures the rate at which real frauds are correctly identified. The F1-score balances out these two things, and all three are vital in places where missing a single fraudulent transaction would be disastrous, and flooding the system with false alarms is similarly unworkable.

Latency and scaling are also top priorities for real-time systems, and because they need decisions made basically instantly, often within milliseconds, fraud detection models that can't keep up can completely clog the system, as Burdick, et al. Pointed out in '14 and Graves, et al. Confirmed in '21. We need to know how well a detection system will perform as the volume of transactions increases, especially during the peak periods and cross-border payments. Streaming architectures, memory-based calculations, and spreading out the load across different machines are all strategies that have been employed to get the latency down to manageable levels, and to make sure that the predictions don't lose their accuracy.

Another area that's very much up for grabs is the handling of false positives, because if there are too many of them, the experience of customers is ruined when they're locked out of their accounts, sending them to complain, and swamping the workloads of the review teams, as seen by Galeazzi et al. In '21. When evaluating the performance of fraud detection and anti-money laundering (AML) analytics in real-time payment systems, a holistic approach is necessary, taking into account accuracy metrics as well as cost-sensitive measures that consider the economic and operational impact of false positives and false negatives.

Techniques like threshold optimization, adaptive risk scoring and sorting high-risk transactions enable financial institutions to cut back on the workload and still stay in line with AML regulations. Coming fast into the world of real-time evaluation also means that fraud detection models must be continually retrained to account for changes in fraud patterns and consumer behaviour, a phenomenon that's been studied by Burdick et al. In '14, and Gao and Ye back in '07. Periodic validation of the models is also required, using streaming data or'sliding windows' to ensure that the performance of the models doesn't deteriorate over time. An operational control panel, alert management systems and automated feedback loops are all necessary components of assessing both the predictive and overall performance of the system.

Empirical assessment of fraud detection and AML analytics in real-time payment systems needs a multi-faceted approach. The precision, recall and F1-score metrics measure how well the models classify the transactions, while latency and scalability are there to guarantee that the models can handle a huge volume of transactions without bogling down. The delicate balancing act of false positives and the hard work they can cause for financial institutions is also given a lot of thought, and continuous monitoring takes care of any new patterns of fraud. Well-known for its thoroughness, these evaluation techniques allow financial companies to understand not only how well their fraud defences are working, but also whether they're operational, and give them the real-time capability to knock out any emerging threats (Bzdok et al., 2017; Burdick et al., 2014; Galeazzi et al., 2021; Gao & Ye, 2007; Ghosh & Reilly, 1994; Graves et al., 2021).

VII. REGULATORY AND GOVERNANCE CONSIDERATIONS

In terms of real-time fraud detection and anti-money laundering, financial institutions have to ensure that the integrity and dependability of their systems are not compromised. One of the biggest challenges being the opacity of automated detection models. Coming from the anti-money laundering regulations, these institutions must be able to thoroughly explain the reasoning behind flagging a transaction as potentially fraudulent and are now fairly well-known for their use of Explainable AI techniques. Feature importance analysis, rule extraction, and interpretable surrogate models in real-time payment systems since 2021.Auditability. Basically the ability to track every transaction, the results of every model run, and the logic behind them all in a coherent manner, is necessary for financial institutions to be in compliance with regulatory requirements, and it's also to their advantage, as accuracy doesn't mean much if they can't go back and check where they got it wrong.

Unfairness and the handling of risk are top priorities in real-time payment fraud and AML analytics. Unfortunately, machine learning and data-driven systems can contain unconscious biases, born from poorly balanced training data, historical injustices, or features that aren't very well thought out, and in real-time payments these kinds of biases can cause one group of people to be unfairly targeted, leading to customer

complaints, legal action and damage to their reputation. Institutions use fairness-aware modelling, rigorously tested models, and real-time monitoring to catch and fix any unbalanced predictions. When setting up a real-time fraud detection and anti-money laundering (AML) system, a predictive model is not enough. You also need a solid governance structure, which lays out the operational processes, and the steps to take for high-risk cases, and verifies that a human can review and intervene in high-stakes alerts, as per Galeazzi et al. In their 2021 paper.

Aligning the system with AML regulations is of utmost importance, and real-time analytics must comply with the US Bank Secrecy Act, the EU Anti-Money Laundering Directives, and the Financial Action Task Force guidelines. The compliance goes beyond generating alerts and requires the inclusion of fixed rules, transaction monitoring criteria, and report filing requirements in real time, in addition to rapidly dispatching Suspicious Activity Reports, and storing files in accordance with the law, and sending serious cases to higher echelons. As per Gao & Ye in their 2007 paper and Bertrand et al. In 2021, these days companies are being asked to show that their AI-driven systems have opened up new avenues of thought on different types of fraud and money laundering and are not violating the law. It's here that we become even more vigilant in updating, watching over and auditing our systems. Well-known principles that underlie trustworthy real-time fraud detection and AML systems contain the promise that only real threats are detected, and that those systems must be transparent, completely fair and perfectly compliant with the law and ethics, and and when we apply clear reasoning, a paper trail and techniques to neutralize model prejudice we can amplify the faithfulness of our systems, safeguard our clients and satisfy the faith of the regulators in a world where transactions happen in an instant.

VIII. CHALLENGES AND LIMITATIONS

The problem of concept drift and changing fraud tactics is a major hurdle, when using fraud detection and AML analytics for real-time payment systems. Since fraudsters adapt their methods to exploit system vulnerabilities, the fraud patterns they create can differ from the historical data used to train machine learning models. As a result, these models that may be performing well at the beginning may deteriorate over time if not continuously retrained or updated with new patterns. The inability of models to follow these real-time changes in the way people's behaviour, which presents itself to transaction data. Well-known experts such as Bzdok et al. In 2017 and Graves et al. In 2021 show us that the only way to effectively combat this, is with the use of robust online learning and automated monitoring systems, but these add to the system's already existing complexities.

The problem of low-quality and labelled data is another challenge we're faced with. Perfectly trained models require top-notch, representative data, but the real-time payment data we're working with is noisy, incomplete and sometimes gets labelled incorrectly. Fraudulent transactions are also relatively rare, meaning that the data we do have is very imbalanced, makes it hard for the models to learn, and sends up the risk of sending honest people into a financial tailspin by labelling their transactions as fraudulent. Coming heading back to label these suspicious transactions can also mean that the truth isn't known until after the fact, which slows down the updating of our models. There are a lot of limitations that stop them from being able to stay on top of brand-new, innovative fraud schemes, when fraud detection and anti-money laundering (AML) analytics are run in real time. Coming rushing into the system's existing framework is no easy feat either, as it requires an enormous amount of data engineering and validation work (Burdick et al., 2014, Gao & Ye, 2007).

Real-time analytics also face operational and financial trade-offs. Low-latency decision-making calls for a lot of computing power, streaming data setups, lightning-fast servers, and memory-guzzling model architectures. Financial institutions have to balance wanting sophisticated models that get the best possible results against the cost of running and scaling these systems to handle a huge volume of transactions. Overly complicated models may give a tiny bit more detection accuracy, but come with slower speeds, lots of false alarms and really unhappy customers. Well-known governance and compliance requirements add even more operational overhead to real-time systems, forcing financial institutions to design their pipelines with the utmost care to make sure that regulations are met, and the system runs smoothly (Galeazzi et al., 2021, Ghosh & Reilly, 1994).

IX. FUTURE RESEARCH DIRECTIONS

Speaking of fraud detection and AML in real-time payment systems, future research must concentrate on the creation of intelligent models that can dynamically respond to the ever-evolving patterns of fraud and money laundering. However, traditional, fixed or periodically retrained models can't cut it anymore, especially when it comes to keeping up with the changing fraud and money laundering strategies. Coming running over in to fill the gap are online and continuous learning techniques, cleverly adjusting threshold values and self-updating risk scores that take into account the results of confirmed cases of fraud and regular compliance reviews. Robustness, drift detection and safe adaptation under regulatory restrictions are all areas that need to be investigated to make sure that adaptive systems stay both effective and trustworthy in the fast-paced world of high-speed payments.

One of the best ways to pump up the effectiveness of fraud detection is through cross-institutional analytics. Since these

networks of fraud and money laundering can span multiple banks and payment systems, individual monitoring by one institution is simply not enough. Secure data sharing, federated learning and privacy-preserving analytics give us the tools to spot coordinated or distributed crime without exposing customers' sensitive information, but more research is required to get past the obstacles associated with governance, interoperability and laws. The final area of growth for the fraud and AML sector is AI-driven compliance automation. Future systems are very likely to contain sophisticated logic that takes care of regulatory reporting, prioritises alerts and manages cases, lifting the load from compliance teams, and research into explainable automation, human-AI collaboration and end-to-end compliance flows can make both more efficient and more legally secure.

X. CONCLUSION

In terms of fraud detection and anti-money laundering (AML) in real-time payment systems, the landscape of instant settlement, continuous availability and tiny windows of time to act pose a unique set of challenges. Combining existing research with in-depth analysis in the field, this study spelled out the distinct risks that real-time payments present, and showed that analytical models, the way systems are constructed and management guidelines need to be brought into harmony to effectively fight these perils. One of the main contributions of the study was a clear and methodical outline of the risks associated with real-time fraud and AML, an integrated vision of analytics that is well-suited to environments where seconds count, and a plain speaking explanation of regulatory and practical issues that come to the surface in real-world implementations. From a hands-on perspective, the results stress the significance of analytics-driven strategies that take into account detection accuracy, processing power and compliance with the law for financial institutions that operate real-time payment systems. Institutions should move away from the traditional batch processing systems and toward streaming analytics, adaptive models and hybrid systems that can leap into action to neutralize threats as they happen.

Just as critical is the integration of transparency, accountability and fairness in fraud and AML systems, in order to earn the trust of regulators and maintain the satisfaction of their customers. Investment in high-quality data, governing bodies and scalable infrastructure is therefore a must-have for sustaining successful risk management in the fast-paced world of high-speed payments. When considering the security of real-time payment systems, a all-encompassing plan is required that combines cutting-edge analytics, ironclad system design, and robust regulatory oversight. As instant payments spread globally, the capability of financial institutions to rapidly and effectively detect and counter fraud and money laundering will be the deciding factor in preserving trust, financial stability and innovation in the payments network.

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