ISSN 2063-5346

A REAL-TIME SELLER SIDE RISK ANALYSIS MODEL FOR EFFICIENT CROSS BORDER TRANSACTION USING BIG DATA

G.R. Srikrishnan[1], R. Durga[2]

Article History: Received: 01.02.2023 Revised: 07.03.2023 Accepted: 10.04.2023

Abstract

The growing use of E-commerce encourages the risk analysis on different side of CBT (Cross Border Transaction). This article focused on analyzing the risks factors involved in the downside of the CBT. Towards this problem there exist numbers of approaches which consider the reputation and popularity as the key factors, which suffer with poor performance. To improve the performance, an Real-Time Seller Side Risk Analysis Model (RSSRAM) is presented in this article. The method considers various factors and analyzes the risk of seller in various ways. The dataset available has been preprocessed at the initial stage. Further, the method applies Turnout Analysis, Feedback Analysis, and Customer Handling Analysis. The method performs turnout analysis which analyzes the average turnover generated in various times of the economic year. Further, the method performs feedback analysis, which considers the feedback obtained from various customers about the service. Finally, the method applies customer handling analysis algorithm which analyze the customer handling behavior of the seller. Each analysis measures different support measures and finally, an risk support value is measured to classify the seller trustworthy. The proposed approach improves the performance of risk analysis on cross border transaction.

Index Terms: CBT, Big Data, RSSRAM, Turnout Analysis, Feedback Analysis, Customer Handling Analysis, Risk Analysis.

[1]Research Scholar, Department of Computer Science, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Chennai, India

[2]Associate Professor, Vels Institute of Science, Technology & Advanced Studies (VISTAS), Chennai, India

[1]grsrikrishnan@gmail.com, [2]drrdurgaresearch@gmail.com

DOI:10.31838/ecb/2023.12.s1-B.253

1. Introduction:

The growth of information technology supports various process of business models. The business process involve in various stages, which must be perfect. It can be noticed in a E-commerce platform, which has various stages like product selection, order placement, payment, delivery, and so on. In this, the entire process involves between two entities like seller and buyer. In most processes, the product delivery will be placed only when the payment has been received. The seller has to deliver the product when the user pays the amount for the product. Here, the risk is for the consumer and if the seller didn't place the delivery of the exact product then the consumer gets suffered.

In case of cross border transaction, the payment from the client side has been moved to the controller which may the reserve bank of the country, and further it would be moved to the destination account. The issue here is, how the transaction is involved in risky as the seller would neglect to send the product after receiving the amount. In this case, if the seller is identified and classified as malicious, then the controller of the E-commerce system would ban the seller in selling product through the forum. Similarly, if the user or consumer is identified as malicious and involve in money laundering, then he would be classified as malicious to take participate in purchasing products through the forum considered. Accordingly, this article analyses various aspects on analyzing the risk factors of seller by analyzing various factors to perform E-commerce solution towards E-commerce solution.

The risk analysis must be performed over the seller before the placement of order and payment. The risk of the seller has been performed in several ways, and it supports the consumer for the selection of seller. Because, the same product has been delivered by various suppliers and there is a need to choose the exact seller for the product. Here, the risk of seller is identified by analyzing various behaviors in various ways. The trust of the seller has been verified according to the reputation, popularity, and so on. But in reality, the sellers like amazon even have the record of poor service which would deliver a wrong product. This really damages the morale of the consumer, which also damages the purpose of cross border transaction (CBT).

The trust of seller should be verified by analyzing the behavior of seller in handling the customer, their turnout in different time, feedback from the consumers and so on. By doing so, the performance of the CBT can be improved. By all these consideration, a novel Real time Seller Side Risk Analysis Model (RSSRAM) is presented in this article.

2. Related Works:

Towards analyzing risk over the seller side, there exists number of approaches in literature. Some of the methods are analyzed in this part.

In [1], the author examines both the antecedents and the impacts of sellers' trust in buyers and their perceived risk of chargeback fraud on sellers' intention to trade with buyers in the context of cross-border e-commerce. To this end, we develop a conceptual model that identifies a set of institutional mechanisms to enhance sellers' trust and reduce their perceived risk. In [2], the author examines those programs to explore the question of whether or not participation in such programs can actually assist small and medium sized firms in overcoming the barriers to cross-border e-commerce transactions. Implications for company decision makers and government policy makers in Canada and the US, with application to other cross-border regions, are discussed.

In [3], propose an alternative approach, based on the multi trait-multi method matrix, to assess discriminant validity: the hetero trait-mono trait ratio of correlations. We demonstrate its superior performance by means of a Monte Carlo simulation study, in which we compare the new approach to the Fornell-Larcker criterion and the assessment of (partial) cross-loadings. Finally, we provide guidelines on how to handle discriminant validity issues in variance-based structural equation modeling.

In [4], discuss common method bias in the context of structural equation modeling employing the partial least squares method (PLS-SEM). Two datasets were created through a Monte Carlo simulation to illustrate the discussion: one contaminated by common method bias, and the other not contaminated. A practical approach is presented for the identification of common method bias based on variance inflation factors generated via a full collinearity test. Our discussion builds on an illustrative model in the field of e-collaboration, with outputs generated by the software WarpPLS.

In [5], a trust model in C2C e-commerce was developed, which incorporates four perspectives, namely, (1) natural propensity to trust (NPT) as a personality perspective, (2) perception of website quality (PWSQ) as a website feature perspective, (3) other's trust of buyers/sellers (OTBS) as an interpersonal transaction perspective, and (4) third party recognition (TPR) as an institutional feature perspective.

In [6], find out what kind of risks corresponds to so called cross-border risk-group and is the most common for internationally designed FinTech business models. Additionally, to determine those business model areas, which are influenced by cross-border risks the most and must be created with focus on avoiding, mitigating or sharing these risks. To achieve the goal the authors interviewed representatives of different FinTech companies. In these interviews, experts were asked to describe the most significant risks and to assess the importance of them for each business model dimension by using the Likert's scale as well as to explain the dependencies and the consequences of their influence on different business model areas.

In [7], the author performs analysis on negative association which is more pronounced in conventional banks than their Islamic counterparts. Possibly owning to the distinctive governance structure and the complexity of the Islamic business model, which requires closer monitoring, Muslim debtholders might depreciate a busy board of directors as it is likely to associate with lower scrutinizing effectiveness. In [8], presents a nonlinear dynamical model of production, warehousing, and sale of fast-moving consumer goods, while respecting the effect of historical values on current changes. The model can be used for planning production, or as part of models dealing with cooperation or competition.

In [9], assesses the effectiveness of lending restriction measures, such as loan-to-value and debt-service-to-income ratios, in affecting developments in house prices and credit. We use data on 99 lending standard restrictions implemented in 28 EU countries over 1990–2018. The results suggest that lending restriction measures are generally effective in curbing house prices and credit. However, the impact is delayed and reaches its peak only after three years. In addition, the impact is asymmetric, with tightening measures having weaker association with target variables compared to loosening measures. The association is stronger in countries outside of euro area and for legally-binding measures and measures involving sanctions.

In [10], discuss that a cross-border framework requires regulatory guidance (policies, manuals etc.), respective compliance training and monitoring. All these requirements make offering financial services in multiple jurisdictions an entanglement of competing requirements and restrictions. In our study, we surveyed over 40 financial institutions to explore how they currently cope with cross-border compliance, as well as their plans to tackle the pain points stalling their growth.

In [11], discuss a small two-country NK model with financial frictions, we show that macroprudential responses in core economies can have destabilizing spillover effects on a financially dependent periphery through interbank lending. We subsequently evaluate a policy rule in which the core regulator internalizes these spillovers and compare it to prevailing national stabilization rule.

In [12], develop new theory by considering the effects of decision speed on decision quality under conditions of environmental munificence, under conditions of dynamism, and under the joint conditions of munificence and dynamism. We test our theory through analysis of multi-informant survey data drawn from top management teams and secondary databases, in 117 UK firms.

In [13], discusses the key enabling technologies applied in blockchain and three types of blockchain structures. Finally, seven case studies of blockchain projects in the maritime and shipping industry are discussed. This paper examines how blockchain is likely to affect key supply chain management objectives such as cost, quality, speed, and risk management. The paper illustrates various mechanisms by which blockchain can help achieve the above supply chain objectives. The paper presents early evidence linking the use of blockchain in supply chain activities to increasing transparency and accountability.

In [14], present a comparison of variables within two empirical exercises using up to eight traditional liquidity proxies and two proposed proxies based on semi-deviations in a sample of NYSE-listed stocks. The first empirical exercise analyzes the relationship between liquidity and implied volatility, showing that increases in implied volatility impacts increases illiquidity. Using a decomposition of the squared VIX, we show that both conditional variance and variance premium components affects liquidity.

In [15], investigates contract design by a firm in a supply chain where the quality of the product delivered to consumers is co-created by the quality decisions of the contract designer (platform firm) and the agent (the service provider) whose inputs need to be coordinated. Revenue is a function of the price charged to consumers, the product quality, and a market parameter which may be private information to the service provider. We focus on a contract with payment terms commonly used by large platforms such as Amazon. The platform firm adopts a menu-of-contracts approach to get the service provider to reveal its private information, resulting in optimal quality effort and price decisions that maximize the expected profit of the platform firm.

In [16], investigates the impacts of network relationships on absorptive capacity dimensions. A quantitative survey among 378 hotel businesses was carried out to measure network participation and relationship quality as well as the absorptive capacity. Regression models reveal that the quality of external relationships and the overall network size implicate access and availability of valuable knowledge and positively affect the organization’s capacity to assimilate and exploit the knowledge in pursuit of innovation.

In [17], redesign a process for educating kidney transplant patients with instructions for post-surgical care. Adopting an intervention-based research (IBR) framework and based on our actions to overcome challenges in implementation and sustainment of the redesign, we revise the current understanding of organizational learning theory. Follow-up observations after our intervention show that the process improvements at the hospital are sustained. We supplement the IBR with quantitative analyses and provide evidence of improvements in health outcomes and satisfaction levels of patients associated with the redesign. These analyses are based on difference-in-difference estimations using data from transplant patients, including a control group from other transplant units.

In [18], examine whether CEO overconfidence could explain cross-sectional heterogeneity in the systemic risk of U.S. bank holding companies. Using measures of overconfidence based on CEOs' options exercise behavior and language used in the Managerial Discussion and Analysis of the 10K-filings, we find that banks with overconfident CEOs have higher systemic risk than their counterparts with non-overconfident CEOs. Banks with overconfident CEOs also have higher holding of private mortgage-backed securities and higher leverage.

In [19], find evidence that the returns to the strategy are connected to the business cycle. Returns are positive in both recessions and expansions, but profitability is higher in expansions. Decomposing asset prices into factor related and idiosyncratic components, we associate a significant portion of returns with exposure to time varying economic factors, consistent with rational asset pricing theories having a role in explaining the profitability of the strategy.

In [20], proposed online hybrid model (OHM) which extensively prevents the possibilities of online fraud, and further, if any possibility is present, then it detects and fixes this possibility. The OHM approach is proposed exclusively for in-auction, non-delivery/merchandise and identity theft frauds. OHM further is applicable to several other online frauds.

In [21], the author used a Multiple Classifiers System (MCS) on these two data sets: (i) credit card frauds (CCF), and (ii) credit card default payments (CCDP). The MCS employs a sequential decision combination strategy to produce accurate anomaly detection.

In [22], develop a hybrid method for risk evaluation and ranking, named Kano-fuzzy-DEMATEL. This new method offers a more accurate way to calculate the degree of relation among each risk factor considering the influence of consumer requirements and deal with uncertain information on risk evaluation, as to determine the risk priority for cross-border e-commerce SMEs. The ranking of risk factors can provide basis for decision-making and improve the accuracy of prediction.

In [23], the author examines the occurrences of the different types of online frauds and where they were committed. Several interesting trends were found to exist in the data set. First, there were seven major types of online fraud. Second, over 50 percent of the online frauds were related to Internet auctions. Third, some types of online fraud appear to happen only in certain geographic areas or states. Fourth, the number of online fraud cases is highest in states and regions with the largest population.

All the above discussed approaches suffer with poor performance in predicting the risk and finding malicious users.

3. Real-Time Seller Side Risk Analysis Model (RSSRAM) Based CBT:

The proposed RSSRAM model first fetches the E-commerce big data. The data set has been preprocessed to normalize the data according to features and values. With the preprocessed data, the method applies turnout analysis which analyzes the average services provided in various times of the economic year. Similarly, the feedback analysis is applied over the data to measure the trust of the seller according to the feedback obtained. Finally, the method applies customer handling analysis algorithm which analyze the customer handling behavior of the seller. Each analysis measures different support measures and finally, an risk support value is measured to classify the seller trustworthy.

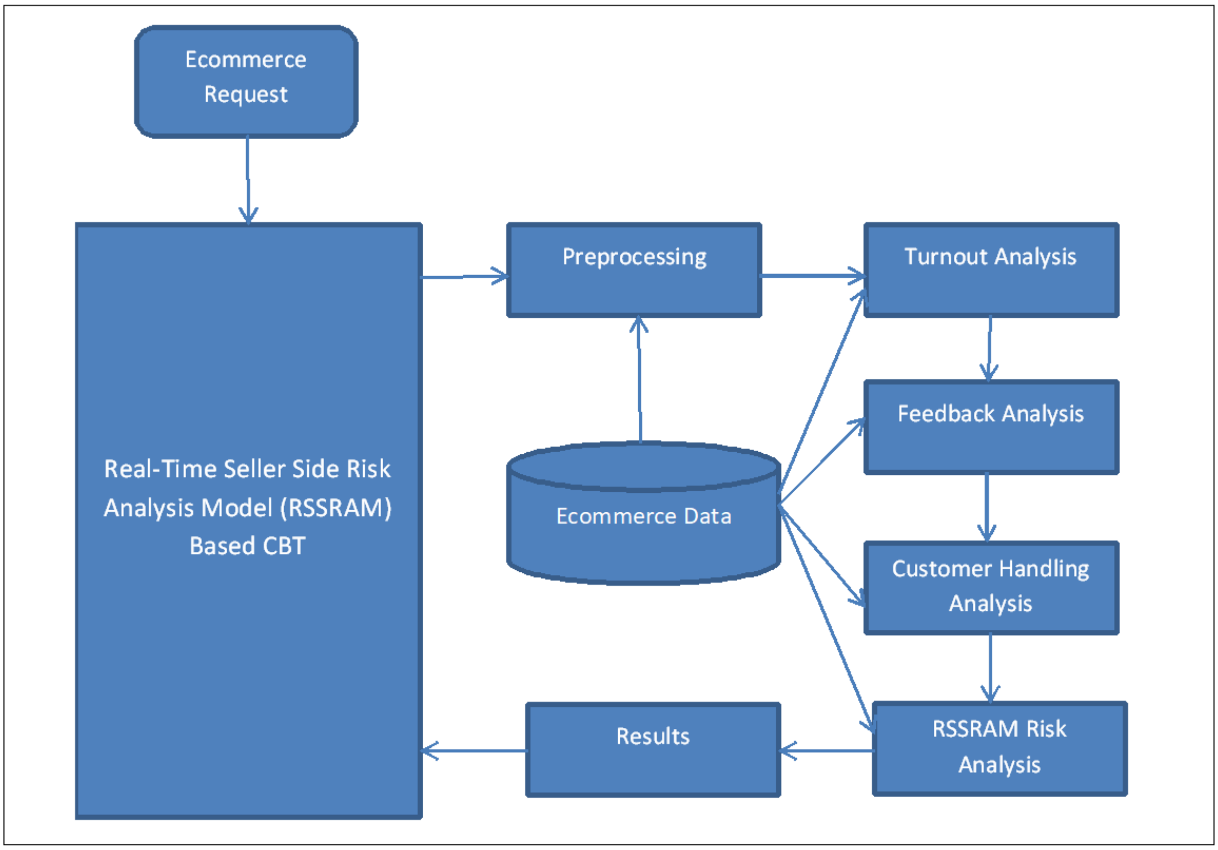

Figure 1: Architecture of Proposed RSSRAM Model

The functional architecture of the proposed RSSRAM model is presented in Figure 1, where the functional components are discussed in detail in this section.

3.1 Preprocessing:

The E-commerce big data contains number of features on different tuples. It also contains large volume of data and some of them would be incomplete on the dimension and values. It is necessary to normalize the data set for the support of risk analysis. To perform this, the method first identifies the set of all features in the data set. Second, each trace has been verified for the completeness of each tuple and the tuples identified incomplete are removed from the data set. The normalized data set has been used to perform risk analysis.

Algorithm:
Given: Ecommerce Data Edat
Obtain: Noise Removed data NRD.
Start
Fetch Edat.
Get Features of data set as Efs $= \overset{size(Edat)}{\underset{i=1}{(Edat(i).Features \ni EFS)}} \cup EFS$
For each Ecommerce data point EDP
If $\overset{size(EFS)}{\underset{i=1}{EDP.contains\ Fed(i)}}$ then
Keep the trace EDP.
NRD = NRD ∪ EDP
Else
Edat = Edat ∩ EDP
End
End
Stop

The above preprocessing algorithm identifies the features from the E-commerce set and finds the noisy records to eliminate from the list. Further, the method generates the noise removed data set towards risk analysis.

3.2 Turnout Analysis (TA):

The turnout analysis is the process of analyzing the performance of the seller in serving number of customers in any time frame. It has been performed by counting the number of services provided in any economic time. Also, the number of services finished in correct way up to delivery of product. Using these two values the method computes the value of Turnout Support (TS) for the seller. Such TS value has been used towards risk analysis later.

Algorithm:
Given: Preprocessed Ecommerce Trace NRD, User U.
Obtain: TS.
Start
Read NRD and U.
Compute total number of service provided TSP = $= Count(\sum_{i=1}^{size(NRD)} NRD(i).User == U)$
Compute Number of services Completed NSC = $Count(\sum_{i=1}^{size(NRD)} NRD(i).User == U \,\&\&\, NRD(i).State == Finished)$
Compute TS = $(\frac{NSC}{TSP} \times 100) \times \frac{1}{TotalGateways}$
Stop

The above discussed algorithm represents how the turnout analysis is performed. The method estimates the Turnout Support for the seller which has been used to perform risk analysis.

3.3 Feedback Analysis:

The feedback analysis is the process of analyzing the feedback of the consumer towards the services provided by the seller. It has been performed by counting the positive and negative feedbacks from the consumer. Using these count values, the method computes the value of Feedback Support value for the seller. Such measured value of Feedback support has been used to perform risk analysis.

Algorithm:

Given: Preprocessed Ecommerce Trace NRD and U.

Obtain: FS.

Start

Read NRD and U.

Compute number of positive feedback NPF = $Count(\sum_{i=1}^{size(PET)} PET(i).Feedback == 1)$

Compute number of negative feedback NNF = $Count(\sum_{i=1}^{size(PET)} PET(i).Feedback == 0)$

Compute FS = $(\frac{NPF}{Size(NRD)} \times \frac{NNF}{Size(NRD)}) \times 100$

Stop

The above discussed algorithm represents how the feedback analysis is performed. The method computes NPF and NNF values to compute the value of Feedback Support (FS). Estimated value of FS has been used to perform risk analysis.

3.4 Customer Handling Analysis:

The customer handling analysis is the process of analyzing the behavior of the seller in providing post service provided by the seller. It has been measured by computing number of products being sold and number of post services provided. Also, the method computes the number of post service tag favor to the seller. Using these two values the method computes the value of Customer Handling Support (CHS) to perform risk analysis.

Algorithm:

Given: Preprocessed E-commerce Trace NRD, User U

Obtain: CHS.

Start

Read NRD and U.

Compute number of products sold NPS = $Count(\sum_{i=1}^{size(PET)} PET(i).Product == Sold)$

Compute no. Of post service provided NPSP = $Count(\sum_{i=1}^{size(PET)} PET(i).PostService == 1)$

Compute No. of Post Service Tag PST = $Count(\sum_{i=1}^{size(PET)} PET(i).PostServiceTag == 1)$

Compute CHS = $(\frac{NPSP}{NPS} \times \frac{PST}{NPSP}) \times 100$

Stop

The customer handling support algorithm analyzes the performance of the seller in providing post services to the user or consumers. It has been measured by computing NPS, NPSP and PST values. Using these values, the method computes the value of CHS to support risk analysis.

3.6 Risk Analysis:

The proposed approach performs risk analysis on any seller by performing behavior analysis on various factors. The method first preprocesses the entire E-commerce data set and applies Turnout Analysis, Feedback Analysis, and Customer Handling. Using the results of each of them, the method computes the value of Trust Support (TrS) to decide on the processing of customer request. Based on the value of TrS, the method performs classification of the seller and selection of seller to get forward.

Algorithm:

Given: Ecommerce Trace ET

Obtain: Boolean

Start

Read ET.

PET = Preprocessing (ET)

TS = Perform Turnout Analysis ()

FS = perform Feedback Analysis ()

CHS = Perform Customer Handling Analysis()

Compute TrS = $\frac{FS}{CHS} \times TS$

If TrS > Th then

Allow

Else

Deny

End

Stop

The above discussed algorithm performs risk analysis according to different behavior of the seller in E-commerce operations. According to the results of different analysis the method performs risk analysis and makes decision.

4. Results and Discussion:

The proposed Real-Time Supplier Side Risk Analysis Model has been implemented and evaluated for its performance under various circumstances. The method uses big data being obtained from the Amazon E-commerce society which covers millions of users. Using the data set, the performance of the methods are analyzed and compared in this section.

Factor	Value
Data Set	Amazon
No of Features	20
No of tuples	1 million
Tool Used	Advanced Java

Table 1: Evaluation Details

The details of evaluation being used towards performance analysis of various approaches are presented in Table 1. According to the features and records, the performance of the methods are measured and compared in this section.

Risk Analysis Performance % Vs Number of Tuples			
	2.5 Lakhs	5 Lakhs	1 Million
Kano-fuzzy-DEMATEL	76	79	82
OHM	78	81	84
MCS	81	84	87
MFFRAM	89	93	97
RSSRAM	91	95	99

Table 2: Performance on Risk Analysis

The performance of various methods in risk analysis is measured and presented in Table 1. The proposed RSSRAM model has produced higher performance than other approaches.

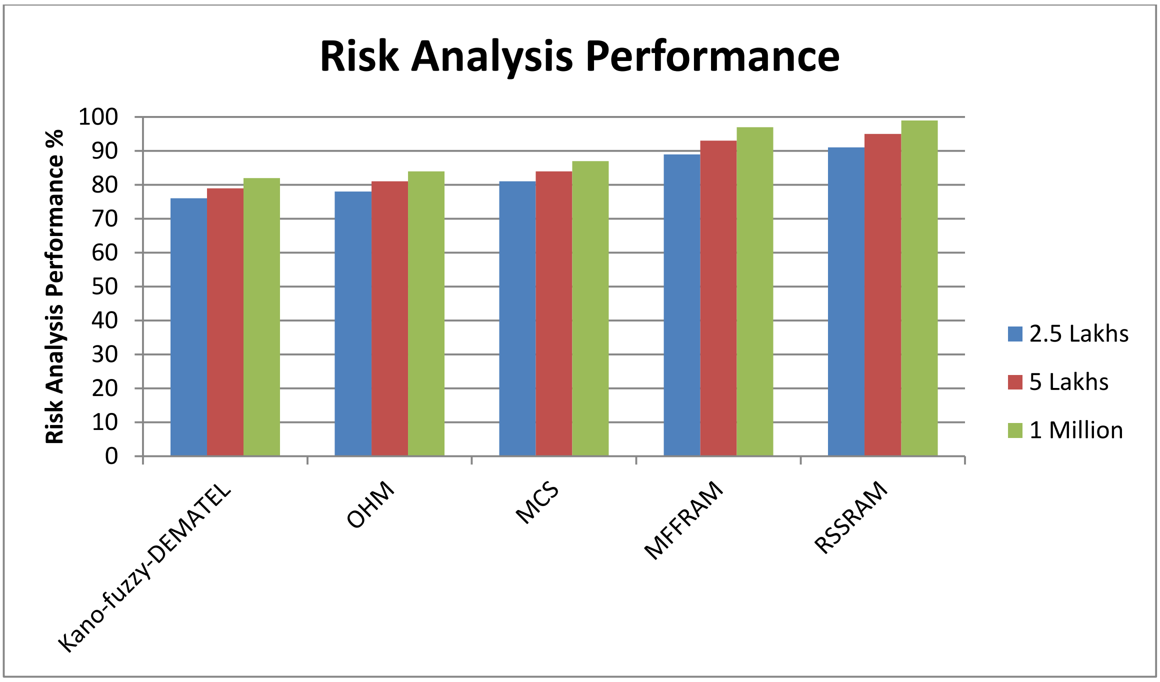

Figure 2: Analysis on risk analyzing performance

The performance of methods are analyzed for various approaches and compared with other approaches. The proposed RSSRAM model has achieved higher performance compare to others.

False Ratio on Risk Analysis % Vs Number of Tuples			
	2.5 Lakhs	5 Lakhs	1 Million
Kano-fuzzy-DEMATEL	24	21	18
OHM	22	19	16
MCS	19	16	13
MFFRAM	11	7	3
RSSRAM	9	5	1

Table 3: False Ratio in Risk Analysis

The false ratio introduced by various methods in risk analysis is measured and presented in Table 3, where the proposed RSSRAM model has produced less false ratio compare to others.

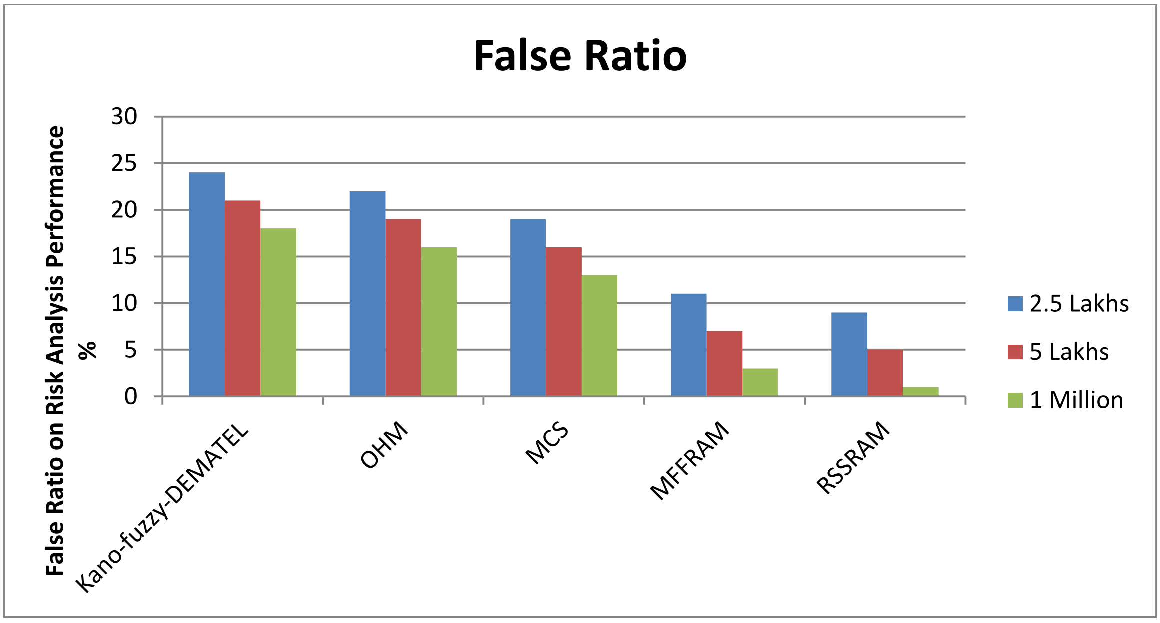

Figure 3: Analysis on risk analyzing performance

The performance of methods in false ratio in risk analysis is measured and compared to others in Figure 3, where the proposed RSSRAM model has produced less false ratio compare to other schemes.

Malformed User Detection Performance % Vs Number of Tuples			
	2.5 Lakhs	5 Lakhs	1 Million
Kano-fuzzy-DEMATEL	75	77	79
OHM	79	81	84
MCS	83	86	88
MFFRAM	88	92	96
RSSRAM	92	95	98

Table 4: Performance on Malformed User Detection

The performance in detecting malicious user by various approaches are measured and compared in Table 4, where the proposed RSSRAM model has produced higher malicious user detection performance than others.

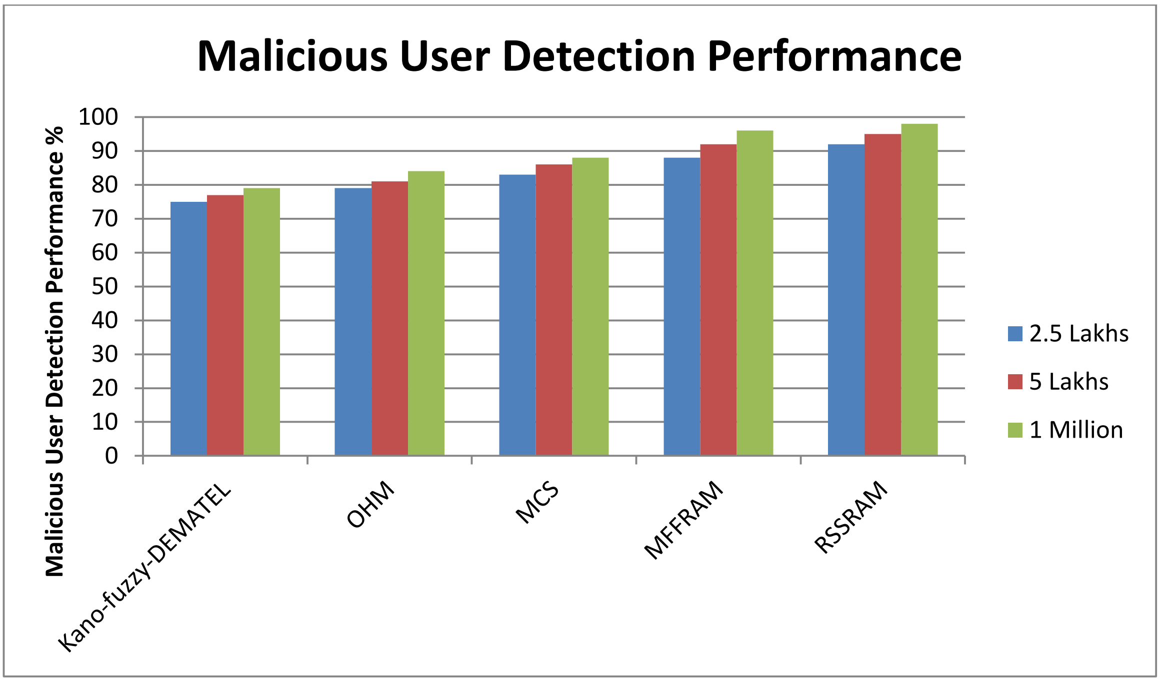

Figure 4: Analysis on Malicious User Detection performance

The performances of methods are analyzed for detecting malicious user in the environment. The proposed RSSRAM model has produced higher malicious user detection performance compare to others.

False Ratio on Risk Analysis % Vs Number of Tuples			
	2.5 Lakhs	5 Lakhs	1 Million
Kano-fuzzy-DEMATEL	25	23	21
OHM	21	19	16
MCS	17	14	12
MFFRAM	12	8	4
RSSRAM	8	5	2

Table 5: False Ratio in Malicious User Detection

The false ratio in detecting malicious user in the environment is measured and compared with others in Table 5, where the proposed RSSRAM model has produced less false ratio compare to others.

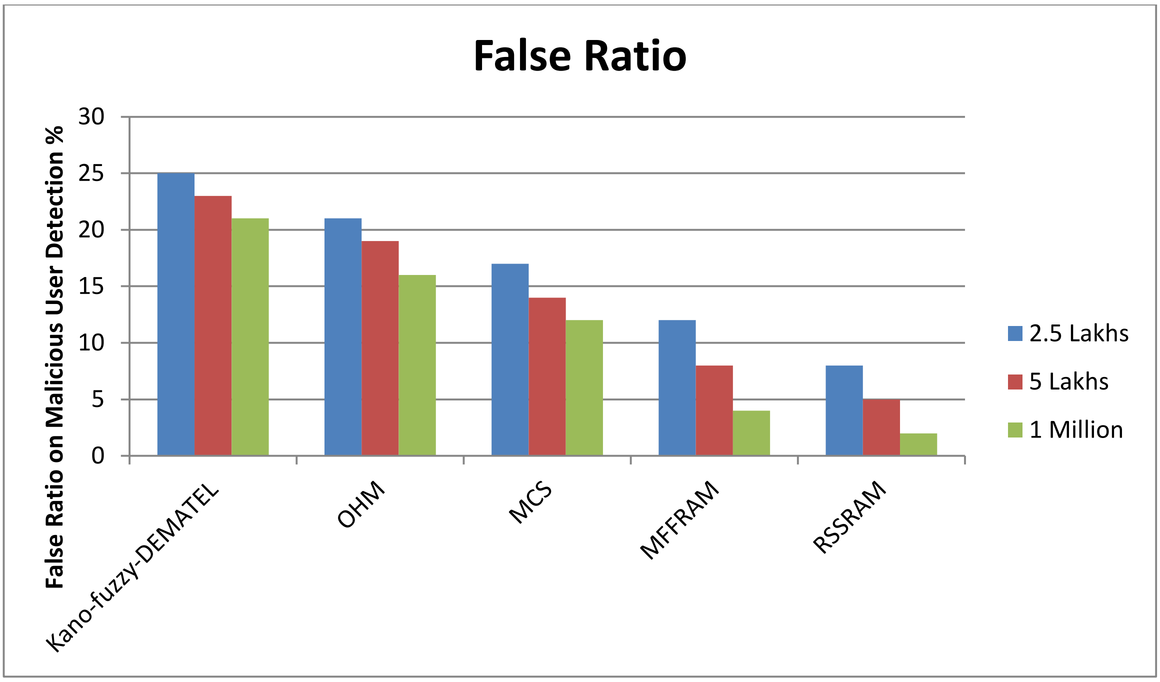

Figure 5: Analysis on False Ratio in Malicious User Detection

The false ratio introduced by various approaches in detecting malicious users in the environment is measured and compared with the other approaches. The proposed RSSRAM model has produced less false ratio compare to others.

4. Conclusion:

This paper presented a novel real time supplier side risk analysis model (RSSRAM) using big data. The data has been preprocessed and the features are extracted. Further, the method performs analysis on various factors like Turnout Analysis, Customer Handling Analysis, and Feedback Analysis By receiving the results from each of the trust analysis, the method computes Trust Support (TrS) to decide on the processing of customer request. The proposed approach improves the performance in malicious user detection and risk analysis towards cross border fund transfer.

References:

1. Yue Guo, Yongchuan Bao, Barnes J. Stuart, and Khuong Le-Nguyen, To sell or not to sell: Exploring sellers' trust and risk of chargeback fraud in cross-border electronic commerce, Wiley, 2017, DOI: 10.1111/isj.12144.
2. Gessner, G. H., & Snodgrass, C. R. (2015). Designing e-commerce cross-border distribution networks for small and mediumsize enterprises incorporating Canadian and U.S. trade incentive programs. Research in Transportation Business & Management, 16, 84–94.
3. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.
4. Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration,11(4), 1–10.
5. Yoon, H. S., & Occeña, L. G. (2015). Influencing factors of trust in consumer-to-consumer electronic commerce with gender and age. International Journal of

Information Management, 35(3), 352–363.
6. Helena Skadina and Vilnis Veinbergs, Cross-Border Risks as an Impact Factor for International Fintech Business Models, SHS Web of Conferences 92, 0 (2021).
7. Trinh, V. Q., Aljughaiman, A., & Cao, N. D. (2020). Fetching better deals from creditors: Board busyness, agency relationships and the bank cost of debt. International Review of Financial Analysis, 69, 101472.
8. Skapa, S., & Novotna, V. (2018). Solving microeconomic model using methods of functional analysis. Economic Computation and Economic Cybernetics Studies and Research, 52, 41-43.
9. Poghosyan, T. (2020). How effective is macroprudential policy? Evidence from lending restriction measures in EU countries. Journal of Housing Economics, 49, 101694.
10. El Fotouh, H.A. (2016). Cross-border Compliance. Retrieved from: https://www.linkedin.com/pulse/challenges-cross-border-compliance-hany-abou-elfotouh.
11. Badarau, C., Carias, M., & Figuet, J. M. (2020). Cross-border spillovers of macroprudential policy in the Euro area. The Quarterly Review of Economics and Finance, 77, 1-13.
12. Shepherd, N. G., Mooi, E. A., Elbanna, S., & Rudd, J. M. (2020). Deciding Fast: Examining the Relationship between Strategic Decision Speed and Decision Quality across Multiple Environmental Contexts. European Management Review, 1-22.
13. Li, L., & Zhou, H. (2020). A survey of blockchain with applications in maritime and shipping industry. Information Systems and e-Business Management, 1-19.
14. Ramos, H. P., & Righi, M. B. (2020). Liquidity, implied volatility and tail risk: A comparison of liquidity measures. International Review of Financial Analysis, 69, 101463.
15. Avinadav, T., Chernonog, T., Fruchter, G. E., & Prasad, A. (2020). Contract Design when Quality is Co-Created in a Supply Chain. European Journal of Operational Research, 286(3), 908-918.
16. Binder, P. (2020). Impacts of network relationships on absorptive capacity in the context of innovation. The Service Industries Journal, 40(13-14), 974-1002.
17. Anand, G., Chandrasekaran, A., & Sharma, L. (2020). Sustainable process improvements: Evidence from intervention- based research. Journal of Operations Management.
18. Liu, L., Le, H., & Thompson, S. (2020). CEO overconfidence and bank systemic risk: Evidence from US bank holding companies. International Journal of Finance & Economics.
19. Hutchinson, M. C., & O'Brien, J. (2020). Time series momentum and macroeconomic risk. International Review of Financial Analysis, 69, 101469.
20. Ankit Mundra, Nitin Rakesh, Online Hybrid Model for Online Fraud Prevention and Detection, Research Gate, 2017, Doi: https://www.researchgate.net/publication/280546238.
21. S. N. Kalid, K. -H. Ng, G. -K. Tong and K. -C. Khor, "A Multiple Classifiers System for Anomaly Detection in Credit Card Data With Unbalanced and Overlapped Classes," in IEEE Access, vol. 8, pp. 28210-28221, 2020, doi: 10.1109/ACCESS.2020.2972009.
22. Shan Dua, Hua Lia, and Bingzhen Sun, Hybrid Kano-fuzzy-

DEMATEL model based risk factor evaluation and ranking of cross-border e-commerce SMEs with customer requirement, IOS Press, Journal of Intelligent & Fuzzy Systems 37 (2019) 8299–8315 DOI:10.3233/JIFS-190830.

23. Lai C. Liu, Kai S. Koong, Margaret Allison, June Wei, AN EXAMINATION OF ONLINE FRAUD COMPLAINT OCCURRENCES, Issues in Information Systems, Volume VI, No. 2, 2005.