Marketing Channel Recommendations in Banking

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***Abstract*—Many industries have applied various analytics techniques to personalize the experience of their customers as well as the offers made to them. Personalization has become the hallmark of every service and product industry even in the once monolithic banking sector. Recommendation systems are a core component of this personalization, focusing on targeting consumers with specific products. Traditional recommendation systems make use of large data sets in sparse matrices while conventional user targeting systems leverage external data sources (e.g., from social media and third parties). Our research focuses on data from a large financial institution and investigates the issue of recommendation systems for channel and product targeting. The proposed system achieves both high performance in channel targeting and acceptable performance in product targeting as illustrated through numerical results.**

***Index Terms*—Business Intelligence, Data Analytics, Classification Model, Binary Classification**

I. Introduction

With advancements in technology, specifically communication infrastructure, internet access, mobile technologies and IoT there has been an explosive growth in data. Estimates place the worlds data at 200 zeta bytes by 2025 compared to our "meager" 80 as of 2021 [1]. This growth has resulted in rapid changes in the commercial market, with big "tech giants", leveraging their data for consumer platforms and targeted operations resulting in the expansion of companies like Amazon and Alibaba. This trend is not isolated to just the big industry players. Most product or service oriented industries are adopting data analytics to augment their operations. Even the once thought of, monolithic baking sector, has changed to pseudo "Fin-tech" in a race to leverage their rich transaction data sets in an ever increasingly competitive field [2].

In reality, the Banking sector has always been on the cutting edge of applying technology, being some of the earliest adopters of the initial computers. Their wide spread use of database software, development of the ATM and now data science is no different. For the past two decades the banking sector has found countless ways to leverage their data, from forecasting stock prices and bonds, fraud detection and personal finance management [2]. Most research from the period of 2000-2010 from developed nations such as the USA and UK focused on what drives the customers choices and activity, focusing on their needs and attitudes. It showed the importance of key characteristics such as efficiency, security, flexibility and personalization as driving factors for the relatively loyal consumer group. Within this period, as internet access became more common, as well as the advancements in mobile and computer technologies, a new demographic emerged within banking. Research began reflecting the value proposition of mobile and internet banking as an alternative channel to traditional brick and mortar with demographics, income level and education level cited as the core driving factors for adoption. Though there are some arguments focused on the impact on customer relationships and the lower profitability [3], these are based on specific metrics and ignore the overall cost saved from the transition as well as the additional advantages in terms of customer flexibility, experience and data generation [4], [5].

Online banking has penetrated most of the market space in the developed nations with up to 95% in some cities like Hong Kong [6]. This is in stark contrast to their developing nation counterparts despite having both widespread internet access, the appropriate demographics and typical income/education characteristics [7]. The primary reason is the culture in which traditional brick and mortar banking pervades [6]. This has a negative feedback cycle as low adoption rates prevent further investment and development of the platforms and result in baring most entries as the products provided or the user experience fail to capture the consumer [5], [8], [9], [10]

This results in institutions possessing fairly structured data sets comprised of transactional data and demographic data exclusively. Therefore the data cannot be feasibly leveraged into traditional recommendations systems as it lacks the breath of products to create a sparse matrix. To compound the issue further, due to privacy, legal compliance as well as the low adoption rate, most institutions are unable to leverage exotic data, such as social media, rendering them unable to carry out in-depth behavioural or attitudinal analyses. The disparity between the data for online and traditional banking however, does lend well if we view the recommendation system as a type of segmentation. Thus for our work we approach it as a binary classification problem the result of which can be used as a form of channel and product recommendation system.

The remainder of the paper is structured as follows. Section II covers the review of recommendation systems used in the industry, Section III covers the dataset extracted and used, Section IV covers the approach used, Section V covers the

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results both exploratory and performance and Section VI covers the review of the results and future works.

II. Related Work

Recommendation systems are not new by any means. They have become synonymous with big tech firms and have formed the basis of operation for companies like Amazon and Netflix. Their implementations, however, vary substantially which enables their widespread application to everything in the product and service sector. Fundamentally, recommendation systems act as a sort of information filtering system based on user preferences and ratings derived from the data [11]. The goal of which is to narrow down the items to the most likely to be adopted by the user. The two core methods that have set the foundation are Content based filtering in which items that are similar to those the user has previously rated highly are recommended. The other is Collaborative filtering where similarities between users dictates recommendations, i.e the system determines the similarity index between users and recommends items that are rated highly between them. Both of these techniques suffer from similar issues of cold start (i.e dealing with new entries whether they are new items in the case of content based filtering that lack ratings or new users in collaborative filtering that have no taste profile [12], [11]).

Hybrid systems which utilize both collaborative and content based techniques partially overcome this but suffer from slightly worse performance overall. Variations on hybrid systems such as demographic filter systems have shown comparatively better performance while also dealing with the cold start issue but makes an underlying assumption of demographic niches having the same preferences [11]. This assumption is case specific and does not generally lend well to fiance where income level and education level are also important factors.

Recently alternative systems have come about to address different use cases. Knowledge based recommendation systems (KBRS) learn a user's taste from items the user previously rated highly, and uses this to recommend new similar items. They can be case based on where the system learns a user's taste from items the user previously rated highly and uses this to recommend new similar items or constraint base where a set of possible solutions (including explanations as to why these solutions were selected) dictates the recommendation [13]. KBRS can actually be applied within fields that require structured answers from data such as moratoriums or loan restructuring and portfolio management [14].

The most recent development within recommendation systems is Cognitive recommendation systems which are capable of leveraging not just user data, but exotic data from social media, third party's and domain expert analysis to understand the user's preferences at a behavioural level and detect changes in user preferences and predict a user's unknown favorites. This is beyond traditional systems as it allows for adaptive behavioural modeling in static or changing environments and has shown remarkable performance at the cost of requiring substantially more complex data requirements and expert behavioural modeling to be hard coded [15].

Regardless of the type of recommendation system, they are all heavily data driven and require vast amounts of interrelated data in an attempt to model the characteristics of our user and garner their preferences. Despite the nature of our application and approach, which we delve into in section III, it is more akin to customer relationship management than recommendation systems. Within the field of CRM segmentation and classification are common tools used to ascertain business insights. RFM is one of the most common analyses in finance where we segment users based on the recency, frequency and monetary size of their transactions and assign a value, normally the customer lifetime value [16]. These values are then used to classify users either by K-Means, SVM or within a more complex model via neural networks [17], [16]. We use a similar approach segmenting our users within two groups, online and offline users, based on the assumption that someone who uses online channel,s either internet or mobile banking, uses them markedly more frequently than the alternative. This assumption is supported by the corpus of literature. We dissect our data into 2 primary datasets for users as discussed in the next section and generate a model for the characteristics of online users. We apply this model to the offline users data set in an attempt to determine the individuals that are most similar to our online ones for targeting. This same approach is used for product targeting creating models for users and non-users of each of the banks online products. This allows us to take an offline user based purely off demographics, subject them to this sequence of classifications or "pipeline" and determine the likelihood of them transitioning to the online platform as well as the likelihood of adopting each of the online products.

III. Dataset Description

The datasets used for our online and product modeling were extracted from a much larger collection of datasets from a large financial institution. The bulk of our data consisted of the demographic information of all users, a snapshot of all brick and mortar transactions across all branches within a 1.5 year period from the fourth quarter of 2019 to first quarter of 2021, a history of online transactions and their respective product (i.e, the institution offers six primary services online each of these services is considered a product for our purpose). We cleaned and extracted two datasets from these based primarily on demographic data. The choice of fields is seated within the corpus of literature focusing on user characteristics such as age and financial characteristics such as occupation and income [18], [19], [20], [21], [22], [17]. The first consist of the institutions users (account type and id), their demographics (gender, marital status, occupation etc.) and classification as either an online or offline user. It consist of 192748 rows and 17 columns. The second consist of all online users, their demographics and classification for each of the six products as either a user or non user. It consist of 130928 rows and 22 columns, similar to the first dataset with the addition of the product information. We are not able to publicly share the dataset as it contains users personal and financial information subject to an non-disclosure agreement.

IV. Proposed Approach

Our approach makes the underlying assumption that someone who uses the online channel is not an avid user of the alternative as supported by most literature. Therefore we created a dataset consisting of all users and classified them as online and offline based on their transaction history where any activity on the online platform classifies them as an online user. With the dataset we can then apply a slew of binary classification techniques to model the system. We choose the technique that has both the best performance metrics (as justified in below) in terms of accuracy, precision, recall as well as the best impact on client targeting. Client targeting refers to the number of individuals the classification algorithm will identify from the offline users to transition to the online platform or the number of individuals who are online customers, who do not use for example product 1 and are targeted by the algorithm for product 1. This is important from a business intelligence perspective as a highly accurate system that transitions few clients is less profitable than a moderately accurate one that transitions many clients. The output of the pipeline can then be pushed to a dashboard for ease of representation as shown in Section V.

A. Binary Classification

Binary Classification is a type of supervised learning that aims to categorize new probabilistic observations into its two categories. There are numerous algorithms but for our purpose we apply the most common 10 methods which include individual techniques and ensemble methods as shown in Table 1. From these 10 we select the best performing 3 with regards to accuracy, recall and precision and determine which performs the best in terms of business intelligence, i.e weighing the relative metrics vs the number of clients transitioned using expert level domain knowledge garnered from the institution. With the selected methods we can then create a pipeline through which the bank can place a client's information and determine their likelihood of adopting the online channel and its 6 products. In the case of product classification our dataset consist of exclusively online users and the distribution within the products, users vs non-users, as expected there is substantial variation. This leads to very large imbalances. To account for this we apply a variety of over and under sampling techniques and choose the best performer in terms of the said evaluation metrics.

B. Evaluation Metrics

Evaluation metrics serve as a means to assess our algorithms performance. Accuracy is considered the standard approach however it does not take into consideration non-uniform class distributions especially for positive minority classes. Class distribution refers to

- TP - True positive
- FP - False positive
- TN - True negative
- FN - False negative

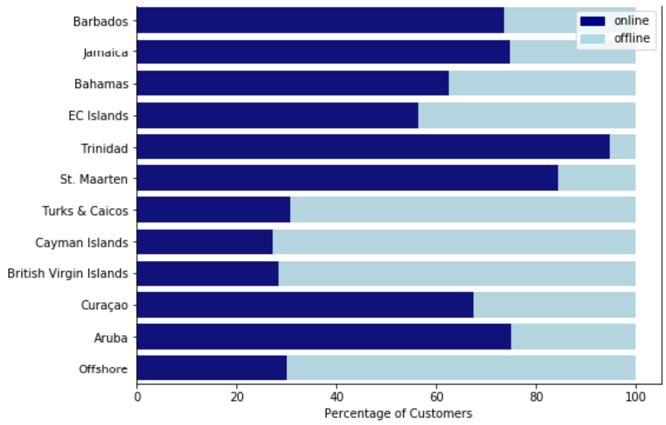

Fig. 1. Online User Distribution by Country

Utilizing the below methods provides a more holistic appraisal as one must consider the business side. Advertisements would be used to target consumers after the pipeline and a high false positive rate would have a negative impact not just in terms of lost revenue but possibly impact the consumers experience as spam etc. Thus we use the following

1) Accuracy: Fraction of correct predictions by the model.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

2) Recall: The number of correct positive predictions.

$$Precision = \frac{TP}{TP + FP}$$

3) Precision: The number of positive predictions that were classified out of all positive predictions.

$$Recall = \frac{TP}{TP + FN}$$

4) F1 score : The harmonic mean of precision and recall.

$$F1 = 2\frac{Precision * Recall}{Precision + Recall}$$

V. Results

A. Exploration

Initial Exploration shows that, despite the initial interest in transitioning customers to the online platform, the average penetration of online banking across the countries in which the bank operates is roughly 50% with variations as shown in Figure 1.

Additionally, when we compare the age variation of the users vs non users as in Figure 2, the distribution seems to support the assumption of the traditional approach to banking especially among the mature population. With offline users

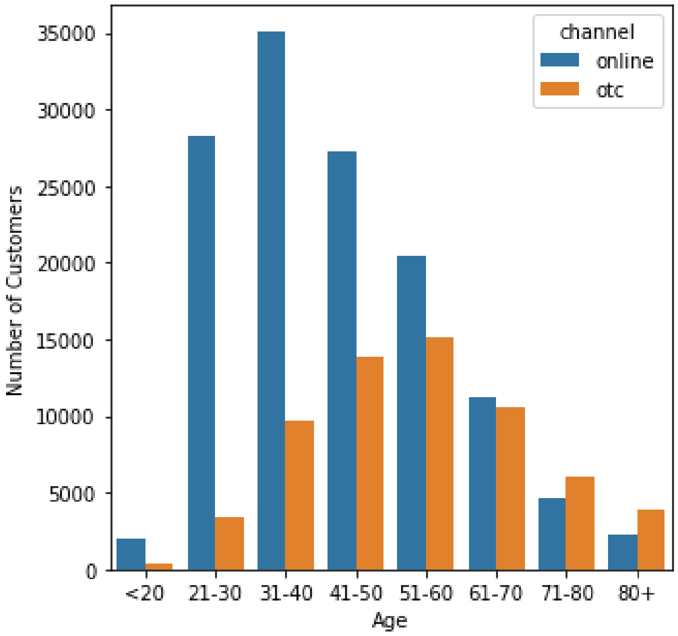

Fig. 2. Age Distribution of consumers by platform

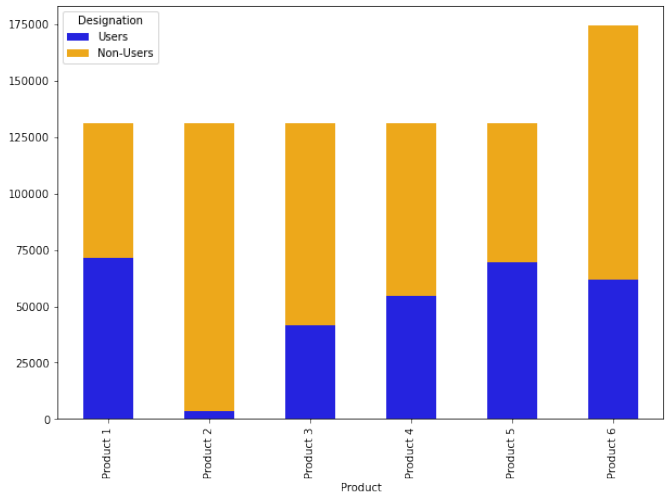

Fig. 3. Distribution of Users by Product

centered around 50-60 years while online users are situated around 30-40 years. This also follows the international trend of the emerging demographics being inclined to mobile banking.

Despite the moderate market penetration of online banking we note that the actual distribution within the products is focused on a few key ones with others being substantially niche (Product 2,3,6). If we consider all individuals that use the online platform as a single population, the ratio of users to non-users for a given product is shown in Figure 3.

B. Performance Evaluation

In the interest of space a sample for each step is shown but the method is applied for each product and channel. For our system we use the two datasets subjecting them to 10 different binary classification algorithms generating evaluation metrics as in Table I. Additionally after reviewing the metrics we take the top three performers and evaluate the number of clients moved. Following our previous sample we get the results as in Table II. In instances with heavily imbalanced data such a product 2 we apply random oversampling, random under sampling, smote. Random oversampling proved to be the best in all instances. The final results from testing our pipeline is as follows in Table III.

The resulting consumer movement can be analyzed in terms of cost saved. Since each transaction users carry out physically in the bank has an associated cost. We can calculate the cost

TABLE I
PERFORMANCE OF CLASSIFICATION FOR PRODUCT 1

Model	Accuracy	Precision	Recall	F1-Score
GBC	65	65	64	65
Hard Voting	64	63	83	71
Random Forest	64	63	63	64
Bagging	63	64	60	60
Boosting	63	64	60	60
LDA	62	62	61	60
KNN	62	61	61	61
Logistic Regression	62	61	60	61
Naive Bayes	61	61	58	58
Decision Tree	60	60	60	61
SVM	52	58	44	67

TABLE II
BUSINESS PERFORMANCE OF CLASSIFICATION FOR PRODUCT 1

Model	Users Transitioned	(%)	Non-Users moved	(%)
GBC	8156	13.1	27869	46.89
Hard Voting	13012	20.9	35749	60.15
Random Forest	4893	7.8	37229	45.81

TABLE III
BUSINESS PERFORMANCE OF CLASSIFICATION FOR PRODUCT 1

Recommendation	Technique
Channel	Logistic Regression
Product 1	Gradient Boosting Classifier
Product 2	Bagging Classifier with Random Oversampling
Product 3	Decision Tree with Random Oversampling
Product 4	Gradient Boosting Classifier
Product 5	Random Forest
Product 6	Random Forest with Random Oversampling

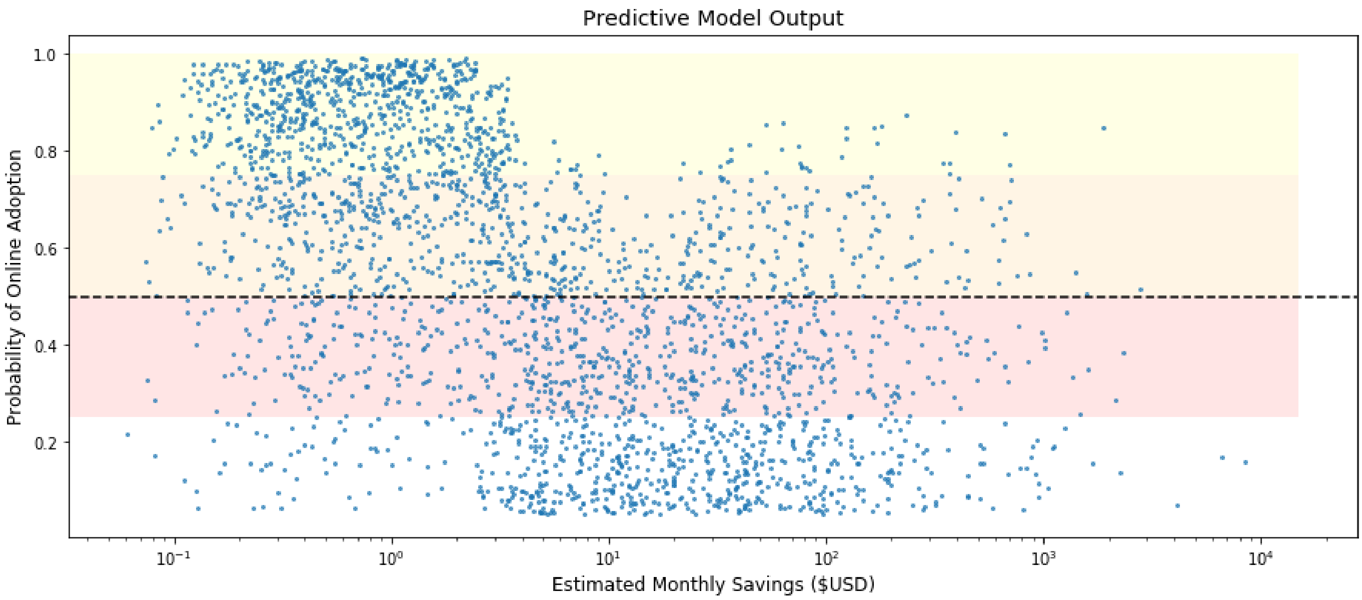

Fig. 4. Cost saved vs Transition probability

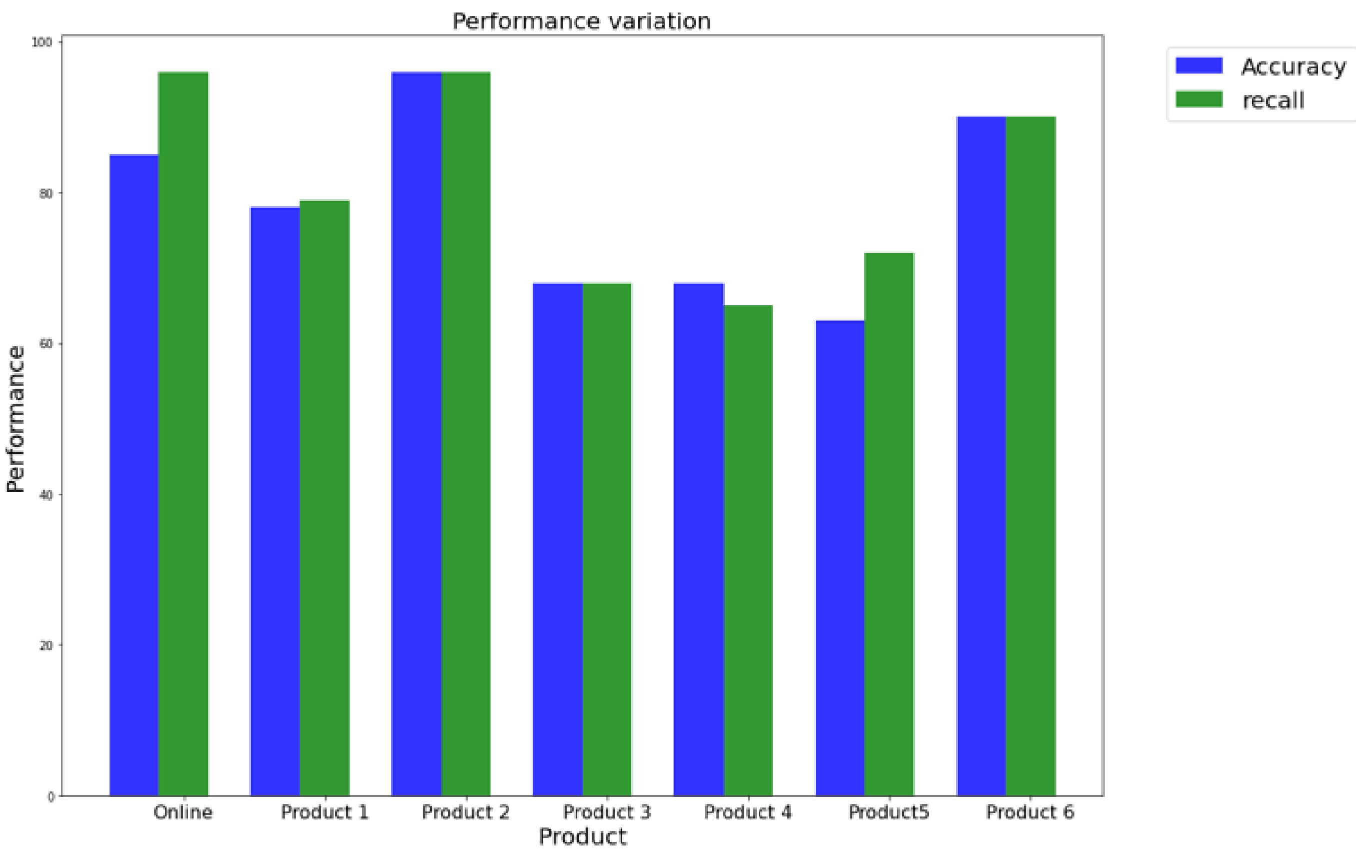

Fig. 5. Performance of each products algorithm

per user and match it to the users transitioned from offline to online system giving Figure 4 We note that there are two main clusters with the most profitable users located in the top left being the least likely to transition. This corresponds to the more mature consumers carrying out transactions in the offline dataset. The second group represents the consumers most likely to transition in the bottom right which are also the least profitable customers. This corresponds to the emerging demographic that does not posses as much transactional power in terms of salary, regular payments etc. These results further lend credence to the traditional approach to banking as well as the younger demographics proclivity for online banking. Reviewing the overall performance in terms of accuracy and recall we get the following graph. Our channel classification system works well with several of the products performing markedly worse but within an acceptable range. These are the smaller datasets with high imbalances.

Lastly we place our systems output through a Tableau dashboard calculating the cost saved based on fixed values. The dashboard shows the possibility of large gains in revenue using the previously discussed cost saved by transitioning clients to the online platform as well as specific gains within certain products. The managerial implication of this research directs more targeted marketing to the identified customers to produce a transition. Additionally there may be possible revenue gain through reduced advertising cost, reduced upfront cost (from the cost of offline transactions) and additional revenue depending on channels which may or have attributed fees.

VI. Conclusion

Our paper has shown an alternative approach to the standard recommendation system using a simple binary classification pipeline. Our method achieved 90% performance in evaluation metrics successfully identifying a large number of clients from the traditional platform to the online channel. Our product classification portion attains substantially lower performance ranging from 65-90% performance in evaluation metrics due to smaller sample size and heavy imbalances within the dataset. Its performance however has been deemed viable for practical applications by the bank for purpose of augmenting their existing systems.

There are however a few limitations to our system. Firstly our data lacked the depth to show user transition, i.e, an individuals history prior to their transition to the online platform. Thus our system may not be ideal for transitioning but rather on boarding of new clients. Secondly the system works well for the transition of customers but makes the underlying assumption that users of the online platform and offline platform are inherently distinct. Even if an individual carries out a single online transaction we classify them as an online user. A better approach may be to replicate the RFM calculations and generate a user score based on their transaction histories or create a type of levied performance metric to better relate online and offline consumers. We can then use this in a multi-class approach to determine users suitability for transition. Lastly the heavy imbalances within the online user dataset leads to low performance evaluation. In the case of very niche products such as the international wire transfers it may be more appropriate to approach it as an anomaly detection problem to attain better overall performance.

References

[1] M. Alnoukari, “From business intelligence to big data: The power of analytics,” in *Integration Challenges for Analytics, Business Intelligence, and Data Mining*. IGI Global, 2021, pp. 44–62.

[2] F. Provost and T. Fawcett, “Data science and its relationship to big data and data-driven decision making,” *Big data*, vol. 1, no. 1, pp. 51–59, 2013.

[3] S. A. Neslin, D. Grewal, R. Leghorn, V. Shankar, M. L. Teerling, J. S. Thomas, and P. C. Verhoef, “Challenges and opportunities in multichannel customer management,” *Journal of service research*, vol. 9, no. 2, pp. 95–112, 2006.

[4] J. Cambra-Fierro, W. A. Kamakura, I. Melero-Polo, and F. J. Sese, “Are multichannel customers really more valuable? an analysis of banking services,” *International Journal of Research in Marketing*, vol. 33, no. 1, pp. 208–212, 2016.

[5] A. Khare, A. Khare, and S. Singh, “Role of consumer personality in determining preference for online banking in india,” *Journal of Database Marketing & Customer Strategy Management*, vol. 17, no. 3, pp. 174–187, 2010.

[6] P. Tangphoklang, C. Tanchotsrinon, S. Maneeroj, and P. Sophatsathit, “A design of multi-criteria recommender system architecture for mobile banking business in thailand,” in *Proceedings of the Second International Conference on Knowledge and Smart Technologies*, vol. 2010, 2010.

[7] C. J. Robinson and W. Moore, “Attitudes and preferences in relation to internet banking in the caribbean,” *Available at SSRN 2848357*, 2011.

[8] A. Sunikka, J. Bragge, and H. Kallio, “The effectiveness of personalized marketing in online banking: A comparison between search and experience offerings,” *Journal of Financial Services Marketing*, vol. 16, no. 3, pp. 183–194, 2011.

[9] F. Calisir and C. A. Gumussoy, “Internet banking versus other banking channels: Young consumers’ view,” *International journal of information management*, vol. 28, no. 3, pp. 215–221, 2008.

[10] L. Wewege, J. Lee, and M. C. Thomsett, “Disruptions and digital banking trends,” *Journal of Applied Finance and Banking*, vol. 10, no. 6, pp. 15–56, 2020.

[11] A. Liu and J. Callvik, “Using demographic information to reduce the new user problem in recommender systems,” *KTH Royal Institute of Technology*, 2017.

[12] L. M. Hitt and F. X. Frei, “Do better customers utilize electronic distribution channels? the case of pc banking,” *Management Science*, vol. 48, no. 6, pp. 732–748, 2002.

[13] G. A. Sielis, A. Tzanavari, and G. A. Papadopoulos, “Recommender systems review of types, techniques, and applications,” in *Encyclopedia of Information Science and Technology, Third Edition*. IGI Global, 2015, pp. 7260–7270.

[14] D. Ball, P. S. Coelho, and A. Machás, “The role of communication and trust in explaining customer loyalty: An extension to the ecsi model,” *European journal of marketing*, 2004.

[15] A. Beheshti, S. Yakhchi, S. Mousaeirad, S. M. Ghafari, S. R. Goluguri, and M. A. Edrisi, “Towards cognitive recommender systems,” *Algorithms*, vol. 13, no. 8, p. 176, 2020.

[16] L. M. Hitt and F. X. Frei, “Do better customers utilize electronic distribution channels? the case of pc banking,” *Management Science*, vol. 48, no. 6, pp. 732–748, 2002.

[17] M. Xue, L. M. Hitt, and P.-y. Chen, “Determinants and outcomes of internet banking adoption,” *Management science*, vol. 57, no. 2, pp. 291–307, 2011.

[18] A. George, “Perceptions of internet banking users—a structural equation modelling (sem) approach,” *IIMB management review*, vol. 30, no. 4, pp. 357–368, 2018.

[19] F. Cai, N. LeKhac, and M.-T. Kechadi, “An integrated classification model for financial data mining,” 2011.

[20] F. Cai, N.-A. Le-Khac, and M.-T. Kechadi, “An integrated classification model for financial data mining,” *arXiv preprint arXiv:1609.02976*, 2016.

[21] H. Hassani, X. Huang, and E. Silva, “Digitalisation and big data mining in banking,” *Big Data and Cognitive Computing*, vol. 2, no. 3, p. 18, 2018.

[22] A. Larsson and Y. Viitaoja, “Building customer loyalty in digital banking: A study of bank staff’s perspectives on the challenges of digital crm and loyalty,” *International Journal of Bank Marketing*, 2017.