V. Result and Discussions

The analyses of the following results are all based on the second dataset provided.

1. Data visualisation and analysis of user consumption habits
2. Daily consumption patterns and cyclical variations

To understand the annual changes in the consumption of the users, a graph of the annual changes in the different types of consumption and income was generated as in Fig. 1. The two curves with the largest amount of change can be clearly observed from the graph: Income and Financialservice&Accommodation. The Income curve shows a triangle-like cyclical variation and peaks at the beginning of each month, which may reflect the timing of payroll. The Financialservice & Accommodation curve, on the other hand, is in a steady state most of the time, while it reaches a trough near June, August and November, most likely related to the end of the school holidays, the end of the summer season and the beginning of the winter season, which may be during the low season for travelling and consumers are more inclined to save. Banks can use this data to adjust the timing of credit products, such as offering overdrafts before a user's salary is paid, or offering special travel loan deals during the low travel season.

In more detail, the categories Personal and Technology&CulturalDevelopment are also cyclical, and the curve of the trend is very similar to income, a consistency that suggests that users tend to spend in these categories as soon as their income arrives. Therefore, banks can introduce reward points or cashback programmes related to these spending categories to encourage users to spend through their cards.

Further, there are some expenditures that do not show significant cyclical changes over time, such as Comprehensive Retail Market, which fluctuates within the range of 0-15,000 throughout the year, as shown in Figure 2. Whereas Figure 3 shows that the Dining&Leisure category rises gradually over time until it reaches its peak at the end of the year, a change that suggests that the increase in savings over time promotes people's spending on dining and leisure. In summary, ComprehensiveRetailMarket's steady spending pattern and the growing trend of the Dining&Leisure category over time offer potential marketing opportunities for banks. For example, banks can promote their partnerships with the RetailMarket and F&B, such as co-branded credit cards or loyalty programmes, to increase user stickiness and meet their long-term needs. The most unusual category is FashionTrend, which, as shown in Figure 4, has an almost irregular curve, with a high probability of guessing that it is related to the aesthetics of the moment.

In addition to looking at consumption patterns on a yearly macro basis, weekdays versus weekends are crucial. Figure 5 illustrates the comparison of total spending on weekdays versus weekends under different categories, with most categories not differing much during the week and on weekends. It is worth noting that more salaries are being paid on weekdays, and banks could develop flexible payroll solutions, such as offering more customised payment day options, including early payment services to suit different customers' cash flow needs. Also, people tend to spend more on fashion on weekends than during the week. Based on this, banks can partner with fashion retailers to offer weekend-exclusive discounts or cashback campaigns via credit card or mobile payment methods to entice consumers to spend on weekends and increase the bank's transaction volume. A step further, Figure 6 shows the comparison between the number of times spent on weekdays and weekends under different categories, and this image can also further confirm that people are more inclined to spend on fashion on weekends.

Overall, these data visualisations and analyses provide banks with important clues to understand their users' spending habits and develop marketing strategies accordingly.

1. Monthly and Annual Consumption Trend Analysis

For monthly income and expenditure totals, frequency and individual transaction amounts, Figure 7 visualises some trends. Vertically, the three graphs on the left represent spending, with January having the highest totals and frequency, a time when banks can help customers better manage their finances by providing budget planning tools and savings accounts. While December was the lowest of the year in terms of both total spending and frequency, but with the highest single transaction value, almost double the usual amount, suggesting that people would only be doing a small, but high-value, amount of shopping over the holidays. These year-end spending habits suggest that customers may need year-end financial planning services, and banks can offer investment advice and tax planning services at this time of year. The three graphs on the right represent earnings, with December being the lowest of the year by almost a third, December has the highest single earnings, suggesting that people hardly ever choose to work over the holidays unless their company is willing to pay a higher salary. This provides banks with important clues about the movement of their customers' money.

Figure 8 visualises the change in balances over the course of a year, where the red dotted line represents the fact that all users arriving at this time have either earned or spent money. It is clear from the graph that the curve is changing cyclically, basically at the junction of every two months there will be a steep rise, and then fall with a certain slope, indicating that people like to spend money after payday, while the macro view of the trend of the whole graph, gradually increasing deposits can be observed, indicating that in general, each month's income is still greater than the expenditure and that the population's deposits are gradually increasing. Fluctuations in annual balances provide banks with valuable information on the flow of customer funds. Banks can develop data-based financial counselling services to help customers manage their funds more effectively, such as automatic transfers to high-interest savings accounts.

1. Consumption Category Distribution and Account-Specific Case Studies

Leaving aside the variation over time, Figure 9 shows a comparison of the total amount of different types of spending, with Health&LivingService at the top of the list, suggesting that there is likely to be a greater market demand for health insurance and healthcare financial products and that banks could develop appropriate financial products to address this. Financialservice&Accommodation and personal also ranked high, indicating that demand for these categories of consumption is also high among the population.

One of the users with the highest transaction volume (858989281) was selected for a comprehensive analysis in Figure 10. By analysing the largest transaction volume user in detail, banks can identify potential high-net-worth individual customers and provide them with customised financial management services such as wealth management and investment advice. Throughout the year, this user's balance gradually increased from about 7,000 to 30,000, and his frugal spending habits can be seen in the barely decreasing curve. His spending habits are focusing on multiple small purchases in March-November and some large and fewer purchases in January, February and December. Although the transaction amount is small, the number of transactions in the categories Dining&Leisure, FashionTrend and ComprehensiveRetailMarket is high, suggesting that these three categories have a small single transaction amount. From the above analysis, it is also possible to make a rough portrait of the user: he is a person who has a regular high monthly income and has no large monthly expenditure other than Financialservice & Accommodation, which indicates that he is relatively regular in his daily life and does not have the habit of squandering. Observing the user's spending pattern after payday, the bank can provide automatic bill payment and budget tracking features to help the customer manage his monthly expenses.

1. Comparison of the predictive performance of different models

In this study, by comparing the performance of different machine learning models in predicting the amount of bank transactions as shown in Table 1, we find that various models are suitable for different banking needs. The following is a further refinement and detailed description of the performance analysis of the above models, with special emphasis on how they can help banks improve their business efficiency and customer satisfaction.

The linear regression model excels with its highest r2 score (0.909) and lowest RMSE (36.5648), which indicates that it has the highest predictive accuracy among all the models tested. The strength of the linear model lies in its simplicity and high interpretability, which makes it well-suited for banking operations where the modelling decision-making process needs to be clearly explained to regulators or customers. For example, in credit approval or financial counselling services, clearly explaining to customers the basis for loan limits or investment recommendations can enhance customer trust and transparency in customer service.

Although SVR and random forests perform slightly less well than linear regression, they demonstrate the ability to capture complex variability in data. Random forests are particularly suitable for dealing with complex data sets that contain a large number of non-linear relationships, and their application is especially important in financial market analysis and asset management. By analysing and predicting market trends or fluctuations in demand for financial products, Random Forests can help banks develop more accurate investment strategies and risk management measures.

With its r2 score of 0.8962 and RMSE of 39.0538, the neural network proves its strong ability to model complex non-linear relationships. For high net-worth customer management, neural networks are able to provide personalised asset management and investment advice by learning in-depth about the customer's transaction patterns, thus helping banks improve service quality and customer loyalty. In addition, this ability of neural networks makes them a powerful tool for preventing financial fraud, identifying abnormal transaction behaviours and supporting the safe operation of banks.

Although the performance of decision trees is not as good as other models, their model structure is intuitive and easy to understand and implement, which makes them particularly suitable for application scenarios with high requirements for real-time trade monitoring and immediate response. However, decision tree models are prone to overfitting when faced with complex or large datasets, and thus need to be used with appropriately adjusted model parameters and pruning strategies to avoid overfitting the data.

1. Bidirectional Interactive Personalised Recommendation Analytics

Better matching of merchants and consumers is also a way to boost consumption.

Figure 11 shows the results obtained after analysing the user's transaction behaviour and account characteristics through clustering, thus providing the bank with a deeper understanding of the user group. With this graph, the distribution of different user groups in terms of income, expenditure and account balance can be visualised, allowing for a better understanding of the characteristics and needs of different user groups in order to recommend potential consumers to merchants. Banks can carry out more precise marketing activities and product positioning based on their in-depth understanding of different user groups. For example, for high-income and high-expenditure user groups with low account balances, banks can launch high-end financial products or credit cards to meet their investment and consumption needs; for low-income user groups with high expenditures, banks can launch flexible loan products or consumer instalment services to help them better manage their funds.

Meanwhile, generating a heat map of transaction frequency as shown in Figure 12 can also help merchants explore potential users. In this heat map, brighter colours mean that consumers are more likely to make purchases in the corresponding merchant category, so merchants can recommend that category of service to potential users. Banks can use this graph to provide recommendation strategies to merchants to help them attract more potential customers.

The same heat map can be used to recommend merchants to users, except that the horizontal axis is changed to users and the vertical axis is changed to merchants, as in Figure 13. Similarly, the brightness of the colours indicates the frequency of transactions between the user group and the merchant, with brighter colours indicating a higher frequency of transactions. Through this graph, we can clearly see the attractiveness of different merchants to different user groups and the frequency of transactions, providing users with the basis for personalised recommendations.

With the above analyses, banks can provide value-added services to their users, such as recommending special offers, new products or merchant discounts. By recommending merchants and products to users that match their consumption preferences and lifestyle habits, banks can increase user satisfaction and loyalty, and increase the frequency and amount of user transactions, thereby increasing the bank's revenue and profitability.

VI. Future Work and Improvement

1. Short-term improvement plan

While current consumption forecasting models have provided effective analysis, further refinement of user profiles is needed, especially for users in different life stages and occupations. By collecting more granular consumption data, such as the user's occupational background, family structure, and lifestyle habits, the consumption behaviour of various market segments can be predicted more accurately. It also helps to identify atypical consumption patterns and increase anti-fraud warning mechanisms.

What's more, the current model relies on the manual entry of large amounts of data, which can be solved by integrating the bank's internal systems and automating external data sources. For example, collecting data on users' consumer behaviour directly from e-commerce platforms and social media through API interfaces will improve data processing efficiency and reduce errors. This automation will also support real-time monitoring, increasing the speed and accuracy of detection of fraudulent activity.

Finally, based on the consumption prediction model, a real-time consumption warning system is developed, which can instantly notify users that their consumption exceeds the budget or abnormal consumption behaviour. The system will help users gain better control of their finances, while also providing banks with the opportunity to intervene in a timely manner to prevent potential credit risks, including timely identification of and response to possible fraud.

1. Long-term development plans

On the basis of current consumer data analytics, it would be beneficial to develop a multi-dimensional consumer analytics platform that would integrate more types of data, including but not limited to social media trends, economic indicators and geographic information, to enable us to understand consumer behaviour from a wider perspective and capture subtle market movements, thereby providing the Bank with the ability to adjust its strategy in different economic scenarios.

Meanwhile, an intelligent financial product customisation and recommendation system can be developed using deep learning and big data technologies. The system will provide personalised financial product recommendations based on the user's consumption behaviour, financial situation and life events (e.g. home purchase, marriage, children's education). This approach not only improves the attractiveness and applicability of financial products but also enhances customer loyalty by providing help when users need it most.

Moreover, if a global consumption database is established, combined with advanced prediction models, such as the neural network that has been successfully applied before, the bank will be able to predict consumption trends in different countries and regions. This will provide data support for the bank's international business expansion, and help the bank make more accurate market entry and product positioning decisions on a global scale.

Finally, in order to cope with rapidly changing market conditions and consumer behaviour, the system of the future will have the ability to learn and adapt itself. By constantly collecting and analysing new consumer data, the model is able to automatically adjust its algorithms and update its predictions in real-time, ensuring that banks are able to respond quickly to changes in the market. At the same time, this technology will also be used to improve the efficiency of anti-fraud systems, enabling them to instantly recognise and respond to emerging fraud patterns.

VII. Conclusion

In this work, based on the second dataset, we first visualised the user's consumption patterns, cycle variations and consumption category distributions in detail, and selected a user with a high transaction volume for a case study. The analysis shows that consumption patterns are closely linked to specific months and events (e.g. holidays), providing an important basis for banks to adjust the timing of their products and services. In the meantime, consumers tend to spend on personal and techno-cultural categories immediately after receiving their salaries, which provides direction for the design of relevant financial products. There are also, through detailed case studies of the largest volume users, we are able to gain a deeper understanding of the spending patterns and financial needs of HNW individual customers, which has important implications for banks in terms of providing personalised services and wealth management advice.

Next, we evaluated the efficacy of various machine learning models such as linear regression, SVR, random forest, decision tree and neural network in predicting the amount of bank transactions. The linear regression model was found to exhibit the highest prediction accuracy among all models and is suitable for application scenarios that require high interpretability. Neural networks and random forests, on an alternative note, perform better in handling large amounts of non-linear data and are suitable for complex market trend analyses. Each model has its unique strengths and limitations, and banks can choose the right model by considering its predictive performance, operational complexity, and fit with business strategy. By implementing these advanced analytics models, banks are able to improve decision-making efficiency, optimise the customer experience and strengthen risk control while ensuring compliance.

Finally, through cluster analysis and heat maps of transaction frequency, we gained insights into the distribution of income, expenditure and account balances of user groups, which helped the bank to more accurately target the market and design personalised products. This method of analysis not only enhances the effectiveness of marketing campaigns, but also promotes co-operation between banks and merchants, enhancing user satisfaction and loyalty. It also allows the bank to gain a share of the merchant's revenue through co-op promotions and transaction sharing, adding a new source of profitability to the bank's business.

Using comprehensive data analytics and advanced machine learning technologies, we have conducted a comprehensive exploration and analysis of bank users' consumption patterns. Through these in-depth insights, banks are able to better understand customer behaviour, optimise product design and adjust service strategies in a timely manner, thereby significantly improving service quality and market responsiveness. Going forward, we plan to continue to expand these analytics to utilise a wider range of datasets and more sophisticated algorithmic models to further enhance forecasting accuracy and operational efficiency, ensuring the Bank's continued leadership in the highly competitive financial market.