Int. J. Nonlinear Anal. Appl. 14 (2023) 1, 2409–2423
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2022.27639.3665

Survey the effect of fintech companies' profitability enhancement on winning customers' loyalty using an artificial intelligence-based optimization algorithm

Mohammad Reza Babakhanian[a], Sayyed Abdollah Amin Musavi[b,*], Roya Soltani[c], Hamid Reza Vakilifar[d]

[a] *Department of Information Technology Management, Qeshm Branch, Islamic Azad University, Qeshm, Iran*

[b] *Department of Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran*

[c] *Department of Industrial Engineering, Faculty of Engineering, Khatam University, Tehran, Iran*

[d] *Department of Accounting, Tehran Science and Research Branch, Islamic Azad University, Tehran, Iran*

(Communicated by Mohannad Bagher Ghaemi)

Abstract

The financial technologies currently known as Fintech refer as a significant innovation to the firms that combine financial services with innovative technologies. More precisely, Fintech means innovative financial solutions enabling novel and creative technologies and methods. Based on the reports by credible international institutions, global investments in Fintech in 2019 have undergone an increase by 120% in contrast to 2018. Therefore, the technological innovation development strategy and the related mechanism and process should gradually create new competitive advantages. Fintech innovations are strategic decisions a given company makes to enhance profitability and win customers' loyalty. The present study investigates the effect of Fintech companies' profitability enhancement on winning the customers' loyalty through a random forest algorithm. The study uses a descriptive-applied research method. The study population included the customers of Asan Pardakht Company, reaching ten thousand individuals with 700000 transactions in number. These individuals (customers) were separated based on clustering operation and classified for being subjected to various tests. Moreover, the cross-industry standard process (CRISP) Method was used, and its various stages were implemented, such as business perception, data perception, data preparation, modeling, evaluation and expansion. After the explication of the data and, also, purging them in various stages and following the data preparation, the data clustering operation resulted in six data clusters that were subsequently subjected to various examinations; the largest cluster (cluster no.4) was finally identified. Afterward, the various artificial intelligence-based optimization algorithms were implemented in the modeling stage. This is usually done with the determination of the accuracy and error rates. The results indicated that implementing the artificial intelligence-based optimization algorithm could enhance the companies' profitability, which affects the companies' winning of the customers' loyalty and satisfaction with the managers of these companies being eventually envisioned as more efficient.

Keywords: Fintech, Customers' loyalty, Artificial intelligence algorithms
2020 MSC: 68T20

*Corresponding author
Email addresses: m.babakhanian@yahoo.com (Mohammad Reza Babakhanian), iranianman2010@yahoo.com (Sayyed Abdollah Amin Musavi), r.soltani@khatam.ac.ir (Roya Soltani), vakilifard_phd@yahoo.com (Hamid Reza Vakilifar)

Received: February 2022 *Accepted:* June 2022

1 Introduction

In the 20^{th} century, financial markets and economies underwent changes in their financial services, especially banking services and products and experienced innovation and technological bursts. Financial technology (Fintech) aims to offer automatic and improved financial services [7]. Financial technology (Fintech) is an evolving concept. As expressed, Fintech is a newly emerging industry that develops technologies for offering and improving well-developed financial services; meanwhile, it also enhances the customers' experiences compared to the traditional delivery models [32]. Industries active in retailing or C2B have adopted Fintech innovations to improve the customers' purchase experience by using them as a customer retention strategy [5]. It is necessary to adopt a Fintech innovation of a type to retain customers [32]. Although various Fintech startups have emerged in the financial services industry, most companies encounter considerable coping and survival problems [6].

Since technology has always played a key role in offering financial services, Fintech companies have adopted more distinct though more detrimental, and usually more customer-oriented viewpoints [25, 26]. Through competition and innovation, it is expected that Fintech companies produce value for the entire financial sector [16]. However, many of these companies struggle not only to enhance profitability but also to survive. Brandl and Hornuf [4] have concluded that the future of digital financial innovations is not determined by technological superiority but by institutional factors. In recent years, these projects' emergence and success have been related to their ability to absorb investment and customer-centeredness. Cumming and Schweinbacher [9] investigated Fintech's patterns of risky investments at a universal level. They figured out that Fintech's risky investment projects are more relatively commonly made in countries with weaker supervision and lacking large financial centers. Cojoianu et al. [8] found that regions with historically intermediate-to-low levels of trust in financial services can only absorb lower Fintech companies' investment. In line with what was mentioned, the present study investigates the effect of the Fintech companies' profitability enhancement on winning the customers' loyalty. The sure thing is that all of the businesses are laid on the foundation of the customers, and their loyalty, with the profitability of the Fintech companies being also interlaced with customers' loyalty.

Because the Fintech companies and their services have been largely and especially welcomed, Gholam Hussein Vala et al. figured out that the initial acceptors of Fintech companies' services tend to be young individuals having large incomes. The high customer-orientation degree and the cooperative collaborations with the financial institutions and electronic trade firms have caused increases in the acceptance of the Fintech companies' services [30]. Fintech companies like Apple and Google use brand loyalty to offer and enhance their financial services. Their access to the data, as well, through the construction of a "comprehensive data ecosystem" along with innovative analytical technologies, allows these giants to offer better services to remain more customer-oriented; hence customers are found consequently more loyal to such companies [19].

Fintechs are instruments enabling the improvement of people's lifestyles and eliminating the various problems of the industry owners and manufacturers. Furthermore, Fintech companies seek to create modern products and services to meet the customers' needs to the maximum possible extent. Thus, to remain in the competition market, they, meanwhile interacting with the customers, should place the carefully-contemplated meeting of their needs atop their work programs [1]. Customers' needs accessibility following the exact recognition of the needs and considering the customers' prior use of these or similar companies' services play an essential role in Fintech companies' profitability. It is by the customers' categorization, investigation, and recognition of the reasons for their various transactions, the time at which a transaction has happened, and even the customers' jobs and age ranges that an essential role can be played in rendering purposive the service-offering to customers. It is noteworthy that each cluster's policies should be separately implemented and executed for every set of customers so that the upgrading of the customer services can lead to the offering of the services in the best possible way. In the meantime, the executive policies should be investigated, analyzed and implemented by elites and experts.

One of the problems in the prior works on the investigation and analysis of the financial services is that most of the prior solutions have been based on statistical and mathematical methods rendering them inappropriate for a large volume of information. Many previous data-mining methods have been used for mathematical analysis of financial services and transactions. They have less frequently come up with smart analysis solutions. One problem with the statistical methods and mathematical analysis are that they are not suitable for a large volume of information that may be consisted of millions of various records and transactions, and the error rate is significantly increased. A solution for this problem is using artificial intelligence techniques that investigate and predict the entering customers' performance. It appears that the use of artificial intelligence instruments in this industry and their large influence on the various financial, banking and trade systems have been followed by the enhancement of the profitability and reduction of a large number of costs for the holders of financial and banking systems. More effective application of artificial intelligence in Fintech companies' financial and banking industries' evaluations can improve efficiency and, eventually, the profitability of the managers and augment the customers' satisfaction. The present study investigates how to reach such efficiency and profitability through a random forest algorithm. In sum, to achieve a high rate of profitability and heighten competitive advantage in the current financial markets, it should be reasoned that the customer-orientation aspect of the financial activities deserves more examination for it includes the recognition of Fintech companies' profitability through winning customers' loyalty. This article aims to deepen the Fintech companies' perception of the customers' loyalty. Based on a collection of assumptions drawn on the foresaid theory, this will be done via statistically analyzing the polling data gathered from the Iranian companies. Thus, the primary problem of this research is investigating and recognizing the profitability of Fintech companies by taking advantage of the customers' loyalty.

2 Reviewing the study's literature

While digitalization has changed the industries, particularly the financial industry, during the past three decades, the global financial crisis became a turning point for the abrupt emergence of the Fintech industry. Ramlall [27] defines Fintech as "financial innovation with digital capabilities." The international organization of securities commission reminds us of "various kinds of innovating business models and newly emerging technologies having the potential of changing the financial services industry." Fintech, digitalization and digital evolution are terms developed after the technological revolution. Darolles [10] recounts financial technology or Fintech as "the application of various kinds of advanced technologies in the financial industry." Digitalization points to the change in the way companies interact with their customers and perform business through novel technologies. Digitalization is the use of novel technologies to create new revenues and opportunities. In this regard, a set of interventions known as digital evolution should be made by the organizations parallel to the adoption of novel and innovative models like meta-data, artificial intelligence and blockchain [20]. Philippon [23] reports that the advent of novel companies (Fintechs) stems from the relatively high cost of traditional channels for offering financial services. Similarly, Frost [12] reasons that there are more motivations for applying Fintechs in economies than the banking sector, which is relatively not competitive.

Fintechs are startups and modern firms that use novel technologies and the internet to offer all the services and ancillaries related to the financial domain and financial services with higher speed and lower cost meanwhile preserving the security and quality of the services. Put more precisely, assisted by creative and modern ideations; these companies play roles in rendering effective all the issues related to financial areas; they apply advanced technology-based hardware and software tools along with innovation to improve the financial services. Passing through the old phase to the modern financial and banking services system, they investigate the risks in the financial transactions and provide the society and even the other startups with proper and sure paths in the financial and banking transactions. Considering the extant needs and applying technology and creativity, these companies try designing and making new and more applicable software and hardware packages in the financial areas [34].

Customers' loyalty is not a new concept, and it has been constantly investigated since the 1930s; since then, many definitions have been offered for this variable. Considering the prior research on the customers' loyalty, authors have suggested that this concept should be recounted as customers' positive attitudes towards the services (and their properties), meaning that they are attitudes that augment customers' preferences within the format of purchasing certain goods and services [33]. The development of customers' loyalty has been considered since its conceptualization by Oliver as an evolutionary and increasing process that started with logical and intellectual proofs (cognitive loyalty) and then changing to emotional attachment (emotional loyalty) and finally behavior (mutual loyalty and practicing it) [11, 21]. Prior research on customer loyalty considers it a hierarchical, daily increasing and cognitive phenomenon. This approach has not accepted customers' loyalty as a meaningful phenomenon in which consumers actively take part in the attribution of meaning to loyalty in various situations [21].

The quality of retaining profitable customers and enhancing customers' loyalty is the companies' perpetual major concern [21]. In competitive environments, as well as in all of the current channels, the costs of the changes are low, and customers can compare the sellers' suggestions and the price levels with more transparency [15]; it seems that customers' loyalty has become increasingly difficult to achieve [14]. Achievement of the customers' loyalty is also of great importance in the Fintech companies. Gimpel et al. [13] showed that Fintech companies, unlike other financial services-providing firms, are outstandingly marked by their adoption of customer-oriented perspectives. Fintech is a dynamic and innovative domain that takes perfect advantage of the progress of information and communication technologies. Customers' experience is a multidimensional concept, so it must be analyzed from various perspectives and consider distinct capacities in different industries [3].

Fintech sector's services are offered with more modern technologies to enhance customers' loyalty, which is a tradition accounting for the recent developments in the Fintech sector [18]. However, academic literature is scarce on this subject. Customers' experiences of Fintechs have been mentioned in several studies that will be dealt with in the upcoming parts. Based on a study about digital banking in England, customers' experiences are positively correlated with their satisfaction; they have also been found to positively influence customer loyalty [17]. The fintech sector brings about more modern technologies to enhance customers' loyalty. It has rendered the traditional model of the financial-banking sector obsolete for its capability of getting closer to the customers [22].

3 A review of the study's empirical background

Carabu Valverde et al. [6] studied the financial and institutional entrepreneurship strategies for Fintech companies' capability to enhance profitability. A thorough population of Fintech-using startups active in Spain from 2005 to 2017 observed that most of these companies start sustaining losses within three years following their establishment. Combining panel data and analyzing the survival rates, they experimentally figured out that large and resolving Fintech companies founded by single entrepreneurs based on a development or acceleration plan were more likely to become profitable and act more superiorly. Fintech Companies were found more rapidly reaching their head-to-head point in case of being funded by an initial capital. Barbu et al. [3] showed that perceived value, customer support, reassurance, speediness and innovation are positively associated with customers' experiences in Fintech Companies. Customers' experiences were also evidenced to positively correlate with their loyalty intentions. This research helps identify the determinants of the customers' experiences and their relationships with their loyalty and clarifies the results of the customers' experiences with the enhanced financial services provided by Fintech companies. This is while they have demonstrated in terms of managerial issues how the Fintech companies should blend customers' experiences in their business models.

Rehman and Ha [28] dealt in a study with the factors influencing the loyalty of Fintech companies' customers to the making of transnational payments with the consideration of an intermediary role played by customer satisfaction. The results indicated that the services' qualities, customers' trust, and products' qualities that considerably influence the customers' satisfaction should be heightened since they are very useful for the current Fintechs that act as home-based versions and also because they wholly constitute a standard by which the performance of Fintechs-applying startups, as well as the traditional banks, can be evaluated so that the latter can be convinced to start utilizing Fintechs in future. In the end, it has also been reasoned in line with succeeding in the competitive markets that concentration on quality of services, customers' trust and quality of products enables enhancing the customers' loyalty to the fintech-applying companies as compared to the other traditional firms so the customers will be more willing to make their international payments through the former companies by the force of such an intermediary variable as the customers' satisfaction. Pramaswari et al. [24] used a data normality test in research in consideration of four variables, namely brand quality, service quality and customer satisfaction, and an intervening variable named fintech-applying companies, to show it based on the data collected from 150 customers that the quality of branding and the quality of services somewhat influence customer satisfaction in the companies using financial technologies with the subsequent increase in these companies' profitability being significantly effective in enhancing the customers' participation. Baber [2] investigated the effect of companies' use of financial technologies (fintech) on customer retention in Malaysia's Islamic banking system. The study's findings indicated that the payments, consultation services and Fintechs' adoption and conformation influence customers' retention.

In contrast, the financial supply services envisioned in the common banking as a significant part were found to have no importance regarding customer retention. The study helps Islamic banks customize the fintech-based services for their customers who would find it subsequently easier to communicate with these fintech-based companies, which can per se grant more value to their financial services. Siek and Sutanto [29] dealt with the effect of Fintechs on the banking industry. Their results signified that the fintech-based startups have digital strategies enabling the adoption of a customer-oriented mentality and the production of goods that together make the customers feel higher satisfaction. Tien et al. [31] investigated the role of customers' behaviors-complying advertisement and their subsequent loyalty to the banks making such advertisements; they also dealt with the role of modern Fintech Companies' technologies as an intermediary variable. In this study, the choice scales were complying behavior, communication marketing and customer loyalty. The model's analytical findings showed that fintech marketing is an intermediary between the customers' behaviors and their transactions' loyalty.

In sum, considering their large volume and vast spectrum of services, Fintech companies can use artificial intelligence to enhance the quality and precision of services and elevate productivity. The more effective application of artificial intelligence in the fintech used in the financial and banking industry can improve efficiency and, eventually, profitability for the managers and end in more satisfied customers. In Iran, steps have also been taken in this regard, but there is a need for more concentration and investment. Currently, the existing Fintech companies are offering services in which the expected mutation and smartness are less traced. Indeed, the existing gap is intensively tangibly felt in such financial and banking technologies and, seemingly, the higher use of the artificial intelligence technologies, meanwhile making customers more satisfied, can be accompanied by an increase in the profitability and satisfaction of Fintechs Companies' managers and owners.

4 Study method

The present study is applied-descriptive research that investigates the variables' interrelationships with the customers' loyalty and uses machine learning techniques to explore the customers' absorption and customers' retention and customers' loyalty when the firms apply financial technologies. The study's stages are explained in Diagram 1.

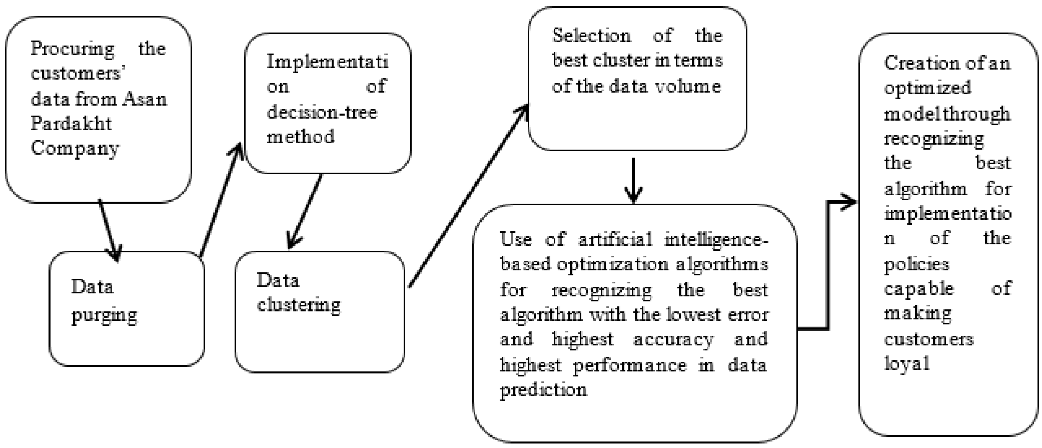


Figure 1: Study's stages

A random forest algorithm is an ensemble using decision trees for its simple and weak algorithms. A decision tree algorithm can easily perform classification operations on a data set while several decision trees, saying 100, are applied in a random forest algorithm. A collection of decision trees creates a forest together, and this forest can make better decisions (as compared to one decision tree).

The study population included Asan Pardakht Company's customers. Because more than twenty million Iranian society members are currently using Asan Pardakht Company's fintech of UP Application, the authors randomly reduced the population to a sample volume of ten thousand individuals with 700 thousand transactions. The customers of the study's sample were separated through clustering and categorized for various tests.

Business Environment: Up is an application developed by Asan Pardakht Persian Company, and the users can make their payments by this application. To use the Up application, the users need their mobile phones to be connected to the internet, and they should also have the second code of their credit or bank card and such specifications as CVV2 and the expiration date of the bank card. Some of the services offered by this application are internet recharging, money transferring from one card to another, SIM card recharging, paying the bills, receiving one's bank account balance sheet, paying mobile phone call charges, charitable endowments, paying for the insurance fees, teleprocessing, automobile services, paying tips for the arrival of the new year to the subscribers, Up Club's membership, investment, Uptel (international phone calls and messaging), buying tickets for the train, bus, airplanes and so forth, receiving scores for the doing of such online transactions by Up Application and so on.

The study data included the transactions done by the Asan Pardakht Company and the interviews with the company's managers and experts.

5 Tests used

In this research, Python Programming Language was used to cluster and perform various data-mining tests on the compiled data by calling on such functions as Numpy, Pandas, Matplot and Seaborn. The primary goal of Numpy is providing the possibility of working with multidimensional homogenous items that are tabulated elements (usually numbers) of the same type indexed through the use of multiple positive integers. In Numpy, dimensions are determined by numbers along the x-axis, with the number of axes termed rank.

Figure 2: CRISP stages

6 Stages of CRISP

CRISP is an abbreviation for a cross-industry standard process that serves data mining.

This research paper generally divides this process into six primary stages: business understanding, data understanding, data preparation, modeling, evaluation and deployment.

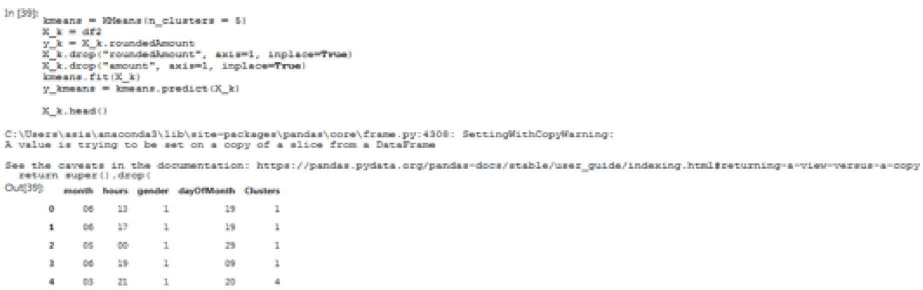
7 Modeling and evaluation

A) Clustering:

Clustering operation was carried out on the data using Python Programming Language and Scholarly Library. At first, the intended library was imported, and then, the properties of interest with numerical values were chosen. Next, the intended model is made using KMeans (n_cluster=5) with the inputted arguments determining the number of the intended clusters. Next, the data are given to the model through Fit Command and clusters are subsequently made. Then, a column named clusters is added to the data frame, and every data record's corresponding cluster is specified. Using Head Command, five preliminary data are investigated.

The constructed clusters are placed on a diagram in correspondence to various data. The following code segment investigates the clustering concerning the amount of SIM card recharging every month during a given year. As observed, the clustering made on the SIM card recharging amounts every month reflects the idea that the lower amounts are displayed in more compact forms, and the clusters become scattered when the recharging amounts are increased.

It is also noted in an investigation of the diagram that the data of higher recharging amounts are fewer in some of the months, such as the fifth one and more in some others, like the sixth or eleventh month.



```
In [39]:
kmeans = KMeans(n_clusters = 5)
X_k = df2
y_k = X_k.roundedAmount
X_k.drop("roundedAmount", axis=1, inplace=True)
X_k.drop("amount", axis=1, inplace=True)
kmeans.fit(X_k)
y_kmeans = kmeans.predict(X_k)

X_k.head()

C:\Users\asia\anaconda3\lib\site-packages\pandas\core\frame.py:4308: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
Out[39]:
```

	month	hours	gender	dayOfMonth	Clusters
0	06	13	1	19	1
1	06	17	1	19	1
2	05	00	1	29	1
3	06	19	1	09	1
4	03	21	1	20	4

Figure 3: Clusters' illustration

As observed, the clusters have been constructed unsupervised through the K-Means method.

B) K-Means Algorithm:

This algorithm divides the data into n groups that have identical variances, and efforts are made in this method to minimize a scale named inertia. This scale is obtained by calculating the sum of the square distances between the data and the mean value of every cluster, and it has to finally reach a minimum amount. The following formula calculates inertia:

$$\sum_{i=0}^{n} min_{u_i \in C}(\|x_i - u_j\|^2)$$

Where n is the number of the data sample's participants, divided by k numbers of separate C clusters, each of which is designated by a mean u_j value, the other name for this mean is the central point or centroid.

Inertia's amount indicates the extent to which the intracluster data are uniform.

After clustering, the frequency of each of the clusters is obtainable in the form of the following table:

Figure 4: Clusters' frequency

As observed in the above-presented clustering, cluster no.4 features the highest frequency. In this regard, and due to the high number of customers in this cluster and because it accounts for the highest profitability in the studied sample, the clustering is continued in a supervised manner based on the title of every datum in cluster no.4. The clustering is carried out here based on the followings:

Every operator and the amounts of recharging made through it

Every operator and amounts of recharging made through it within a month

Every operator and the number of recharging made per every day of a month

Every operator and the number of recharging made during every hour of a day

Customers' gender compositions

Individuals' education levels concerning their amounts of purchases

Building or enhancing loyalty concerning the customers' amounts of purchases and transactions.

C) Using Artificial Intelligence-Based Optimization Algorithms for Predicting and Identifying Loyal Customers:

In the previous sections, stages of CRISP were implemented, including business understanding and data understanding, in the initial stage of this research; then, in the clustering section, cases of data preparation, including data purging and data conflict resolution, were exhibited. In this section, machine learning methods will be utilized to present a cumulative display of the customers' data so that, meanwhile reducing scattering, every customer's operations can be specifically determined separately for every transaction per various months. The goal is the determination of the rates to which the application is applied, and the purchase operations are made for the fact that the amount and the number of purchases can be a scale predicting the customers' loyalty; for instance, mobile number 0 belongs to a customer who has used the application for making purchases for 140 times during a year; the customer's purchases have been lowest during June and highest during October, November and December. In this way, various results can be accordingly inferred based on the customer's purchases based on which measures can be taken to enhance the loyalty and purchases. Generally, considering the explanations related to the modeling stages in CRISP, efforts will be made in the forthcoming section to provide the various machine learning models with the data prepared in the previous sections so that the prediction operation can be run on the new datasets via training the proposed model.

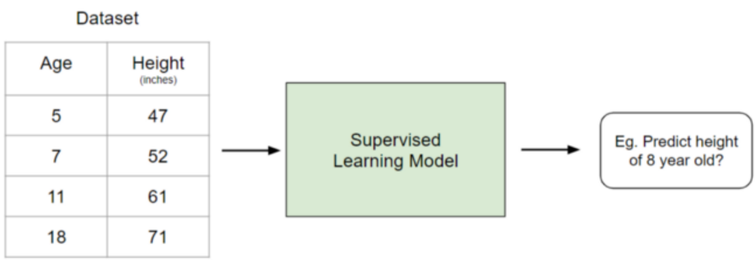


Figure 5: Predicting the new data using machine learning

To perform the prediction operation, various methods are tested, and the best model will be chosen through evaluation methods. In fact, in this section, various artificial intelligence (AI)-based optimization algorithms are utilized to make a model capable of predicting the customers' loyalty and profitability regarding their use of Up application as a fintech company. If the operation is properly and correctly carried out on the dataset, the customers' loyalty rates, as well as the amounts of their future purchases, can be predicted; then, based on every customer's loyalty, plans can be made for their retention and also for offering specific services to them by which the company's influence in the market can be heightened. To do evaluations when creating the models, the mutual validation method has been utilized for the applied data, which should be divided into two sets of test and validation data, after which the model's performance will be ensured about the unseen data. In other words, all of the following algorithms will be subjected to prediction error and accuracy tests based on 80 test data and 20 result validation data.

Polynomial regression

```
In [99]:
from sklearn.preprocessing import PolynomialFeatures

poly_reg = PolynomialFeatures(degree = 2)
X_poly = poly_reg.fit_transform(train_X)

poly_reg_model = LinearRegression()
poly_reg_model.fit(X_poly, train_y)
predictions = poly_reg_model.predict(val_X)
print("Mean Absolute Error: " + str(mean_absolute_error(predictions, val_y)))
print(" accuracy: " + 100 - str(Cross-Predicted Accuracy:(predictions, val_y)))
```

Figure 6: Polynomial regression

1) Decision Tree:

Decision tree is a map of the contingent results obtained from a series of related choices. It enables an individual or an organization to assess the possible interventions in terms of the costs, probabilities and benefits. A decision tree can be utilized for advancing personal and informal objectives and programs or delineating an algorithm capable of predicting the best option based on mathematical calculations. A decision tree is usually commenced from an initial node out of which the contingent outcomes stem in the form of branches, each of which ends in another node that per se creates branches of different probabilities, with the total branched structure being a diagram in the form of a tree.

In the above section, the data pooling and the use of decision tree functions indicate the purchase predictions by the initial customers for rates of 140, 9, 168, 23 and 1 as the outputs. To investigate the accuracy or inaccuracy of the future purchase predictions made by the decision tree, the output data are compared with the real data so that the amounts of the prediction errors can be determined.

Calculating the error of our model with MAE (Mean Absolute Erro

In [92]:
```
from sklearn.metrics import mean_absolute_error

predicted_user_purchases = charge_purchase_model.predict(X)
mean_absolute_error(y, predicted_user_purchases)
```
Out[92]: 0.0

Figure 7: Calculation of the models' errors based on mean absolute error (MAE)

In this section, the model is evaluated. As observed, the amount of the predicted data's error is zero because zero error introduces a phenomenon called overfitting. In the world of algorithms, the goodness of fit means that the algorithm can only make predictions based on the data with which it has been trained, and the algorithm with documented overfitting cannot find a proper response for quantitative data with a little difference from the train set. Hence, it usually, in such cases, erroneously predicts and classifies. It cannot give any precise information by which the model's performance can be evaluated when it is provided with unknown data. The available data are divided into two sets of training and testing data to prevent such cases. The model is trained with the former and evaluated with the latter.

Such an evaluation operation in which overfitting is prevented is called mutual validation, the concept of which was explained before.

Mutual validation has been carried out in the following code segment through the use of the Sholarly Library in Python and the insertion of train_test_split method.

In [93]:
```
from sklearn.model_selection import train_test_split

#Splitting our data into train and validation parts
train_X, val_X, train_y, val_y = train_test_split(X, y, random_state = 1)

# Define model
charge_purchase_model = DecisionTreeRegressor()
# Fit model
charge_purchase_model.fit(train_X, train_y)

val_predictions = charge_purchase_model.predict(val_X)
print(mean_absolute_error(val_y, val_predictions))
```
8.097024052181004

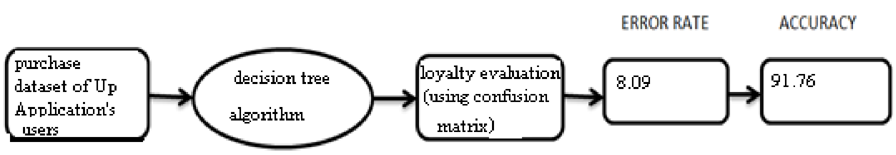


Figure 8: Predicting customers' loyalty and their profitability in the system using error and accuracy rates

As it is seen, this time, a large amount of error is created with the change in the test data indicating the improper performance of the algorithm for predicting the customers' loyalty. Therefore, we need to use other machine learning algorithms to obtain better results.

The investigation and prediction of the customers' loyalty through the use of various AI-based optimization algorithms:

In this section, various AI-based optimization algorithms are applied to optimize the prediction of customers' loyalty and profitability based on the error rate and accuracy rate items for which values equal to 8.09 and 91.76% have been respectively computed as the outputs.

In an investigation of the error and accuracy rates for the largest cluster, the existing data are divided into tests and result in data for respectively 80% and 20% and, then, the decision tree is applied to make predictions about the customers' loyalty and their future purchases; next, specific plans can be made based on every customer's loyalty in regard of customer retention as well as the offering of customer-specific future services which enable the company to enhance its influence in the market. The prediction of the customers' purchase and loyalty rates is highly erroneous and less accurate. The forthcoming section uses other AI-based optimization algorithms to predict the customers' purchase and loyalty rates.

2) Random Forest:

```
In [94]:
    from sklearn.ensemble import RandomForestRegressor

    forest_model = RandomForestRegressor(random_state=1)
    forest_model.fit(train_X, train_y)
    purch_preds = forest_model.predict(val_X)
    print(mean_absolute_error(val_y, purch_preds))

3.0087566245413777
```

Figure 9: Random forest

Random forest is considered a supervised learning algorithm. As it is understood from the name, the algorithm haphazardly builds a forest. The forest includes a group of decision trees. The task of forest construction is often done using trees through the bagging method. The main idea of the bagging method is to apply a group of learning models to increase the model's general results. In simple terms, the random forest method grows several trees and blends them to enable more accurate and stable predictions.

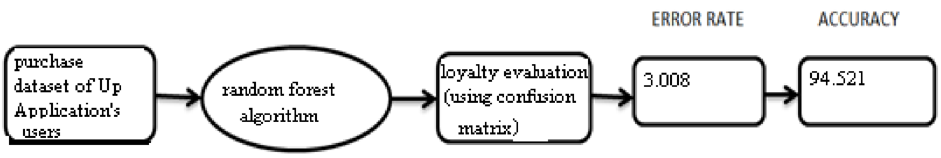


Figure 10: Investigating the customers' loyalty using a random forest algorithm

One benefit of the random forest is its applicability for the classification and regression analysis as two problems of a vast majority of the current machine learning systems. Here, the predictions are assessed in terms of error and accuracy rates which have been computed equal to 3.008 and 94.521% as the outputs. In an investigation of these rates, the data in the largest cluster are divided into test and result datasets for 80% and 20%, respectively. A random forest algorithm was applied to enhance the error and accuracy of customers' loyalty and future purchase rate prediction, thereby coming up with customer-specific plans regarding retention and offering unique services so that the company's influence can be elevated in the market. In this evaluation, it was found that the existing algorithm features a higher prediction accuracy rate than the other decision tree algorithms.

3) Support Vector Machine Algorithm:

Support vector machine algorithm or support vector machine is one of the very common algorithms and methods in data clustering. The support vector machine is also applicable for regression problems. However, it is more utilized in classification problems. In the support vector machine algorithm, every datum is delineated as a point in an n-dimensional space (n being the number of the properties), with the value of every point being the amount given to the point within its coordinates. Scholarly Library is applied to implement the support vector machine in Python. The support vector machine algorithm has been trained herein based on the data available to Up Application.

Here, the prediction accuracy and error rates are assessed to determine the model's prediction power when using the support vector machine algorithm. As it is seen, the error and accuracy rates have been found equal to 5.476 and 94.203%. In this examination, the data of the largest cluster have been divided into test and result data, respectively for 80% and 20%. The support vector machine algorithm was trained using the abovementioned data to see the error and accuracy rates of the algorithm's predictions about the customers' loyalty and purchase rates so that plans can be case-specifically made for customer retention and offering unique services, thereby increasing the company's influence

Support Vector Machine - SVM

```
In [95]:
from sklearn import svm

regr = svm.SVR()
regr.fit(train_X, train_y)

purch_preds = regr.predict(val_X)
print(mean_absolute_error(val_y, purch_preds))

5.476951372659529
```

Figure 11: Support Vector Machine Algorithm

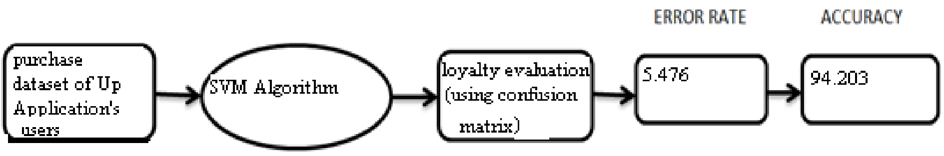


Figure 12: Investigating the customers' loyalty using the support vector machine algorithm

in the marketplace. As observed, the error and accuracy rates have been calculated as nearly equal to those of the random forest.

4) XGboost Algorithm:

XGboost

```
In [96]:
from xgboost import XGBRegressor

my_model = XGBRegressor()
my_model.fit(train_X, train_y)

Out[96]:XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1,
             colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
             importance_type='gain', interaction_constraints='',
             learning_rate=0.300000012, max_delta_step=0, max_depth=6,
             min_child_weight=1, missing=nan, monotone_constraints='()',
             n_estimators=100, n_jobs=16, num_parallel_tree=1, random_state=0,
             reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
             tree_method='exact', validate_parameters=1, verbosity=None)
In [97]:
predictions = my_model.predict(val_X)
print("Mean Absolute Error: " + str(mean_absolute_error(predictions, val_y)))

Mean Absolute Error: 4.530060833369379
```

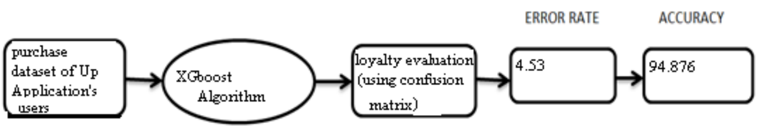


Figure 13: Investigating the customers' loyalty using the XGboost algorithm

One well-known gradient enhancement algorithm is XGboost, which makes win-or-lose decisions in some Kaggle competitions. XGboost features a very high prediction power, making it the best choice when the accuracy of the various events' predictions matters. That is because it covers both linear models and tree learning algorithms. XGboost algorithm is almost ten times faster than the other gradient enhancement algorithms. The algorithm incorporates various objective functions, regression analysis, classification and ranking. One of the most interesting points about XGboost is that it is also recognized as a regulated enhancement technique. The algorithm contributes to the downsizing of the large models and provides a good deal of support for a vast spectrum of languages like Scala, Java, R, Python, Julia and C++. The algorithm supports distributed and scattered training in various systems and encompasses JCE, EWS, Ajuro and Yarn clusters. XGboost can be blended with spark, flink and other cloud data systems constructed based on mutual validation in every reiteration of the enhancement process.

The algorithm has been run herein to assess the prediction accuracy and error rates for which values equal to 94.876% and 4.53 have been attained as the outputs. In this examination, the data of the largest cluster have been divided into test and result data, respectively for 80% and 20%. The XGboost algorithm was trained using the abovementioned data to see the error and accuracy rates of its predictions about the customers' loyalty and purchase rates so that plans can be case-specifically made for customer retention and offering unique services to increase the company's influence in the marketplace. As observed, the error and accuracy rates have been calculated as nearly equal to those of the two algorithms above. It has been predicted through the XGboost algorithm that the customers will make four more or fewer purchases in contrast to their last year's purchases with a guess accuracy rate of 94.87%. As predicted, the customer numbered 0 is supposed to make about 136 purchases as their lowest purchase and 144 purchases as their highest purchase rate.

5) Linear Regression Model:

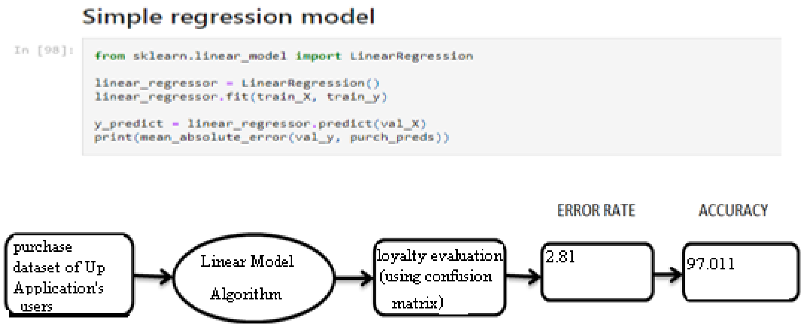


Figure 14: Investigating the customers' loyalty using a regression algorithm

A linear regression algorithm is a supervised learning machine performing linear regression analysis. This regression model predicts a value based on the independent variables. It is mostly applied to determine the relationships between the variables and predictions. The regression analysis models differ based on the relationship between the dependent and independent variables. Linear regression analysis is a common method that serves the investigation and analysis of the statistical data as well as the linear relationship between the dependent variables and one or several independent variables. In addition, the linear regression models are divided into simple regression and multiple linear regression analysis methods. In the former, the independent variable predicts the dependent variables' changes. In the multiple linear regression analyses, two or several independent variables are utilized for predicting the dependent variables' changes. The simple and multiple linear regression methods differ in the number of independent variables used for predicting a dependent variable's variations.

This algorithm's accuracy and prediction error rates were assessed herein, and values equal to 5.476 and 93.498% were obtained as the outputs. In this examination, the data of the largest cluster have been divided into test and result data, respectively for 80% and 20%. The linear model algorithm was trained using the abovementioned data to see the error and accuracy rates of its predictions about the customers' loyalty and purchase rates so that plans can be case-specifically made for customer retention and offering unique services, thereby increasing the company's influence in the marketplace. As observed, the accuracy rate has been slightly lower than that of the foresaid algorithm. It is computed using the linear model algorithm that customers may make approximately 5.5 more or less purchases in a year compared to the last year, with the guessing accuracy being about 93.5%.

The following table gives the error and accuracy comparisons for the models developed herein:

The implementation phase includes using the proposed model in a system to score or group the newly inputted data depending on the problem's type. This will be done in future research considering the nature of the Up application's problems and requirements, as well as the need for assessing the managers and customers' feedback and also evaluation of the customers' loyalty.

6) Conclusion and Suggestions:

In the current study, the accuracy and error rates of various artificial intelligence (AI)-based optimization algorithms were assessed for extracting a model enabling the determination of the customers' loyalty with the consideration of the objectives posited at the beginning of the research as well as the accomplishment of these objectives based on the data procured from Fintech Company following the clustering of the customers in the course of CRISP methodology's implementation. The model's outputs were obtained after the implementation of the model in Python. The results

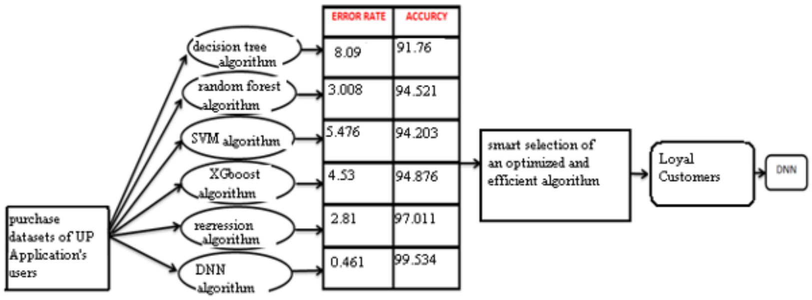


Figure 15: smart selection of optimized and efficient algorithms

indicated that DNN is the most superior of the tested algorithms for optimizing the customers' loyalty, for it was found with the lowest error and highest prediction accuracy. So, it can be concluded that the authors have been able in this research to use this algorithm to find out the best cluster of customers and assess their loyalty when various marketing policies are utilized. In the meantime, this algorithm can also be applied to identify the less loyal customers or the others with less willingness to make purchases through fintechs-applying companies and applications to come up with incentives to make them loyal to the use of the application. It seems that the current findings that have been obtained through the AI-based optimization algorithms highlight the effectiveness and accentuate the role of fintechs' smartification more than ever before. It is a win-win role capable of increasing the number of customers and their purchase transactions. It can be accompanied by an enhancement in the company managers' profitability. This way, these fintech methods can be largely welcomed by the general public in case they are trained more comprehensively and equipped with more effective fascinations. The best optimization algorithm's identification based on its prediction error and accuracy rates and general performance and the subsequent accomplishment of the study objectives are effective in producing sciences. In such studies, the prediction type and method can be enhanced in line with the elevation of the customers' loyalty following the recognition and upgrading of the best optimization algorithm so that the marketing science can be better served.

7) Further recommendations and suggestions:

Considering the data investigation using AI-based optimization algorithms in this research and knowing the increasing daily needs of the society members for the electronic financial services, the following are some recommendations and suggestions that can be examined in future research.

A) Applied Suggestions:

1. Considering the prominent role of fintech in expanding the use of AI-based optimization algorithms, it is suggested that newly entering customers' information banks should be created to determine the clusters with the highest number of customers and transactions, and then predictions should be made based on this information; next, the accuracy and error rates of the predictions should be consequently evaluated thereby to compare the real and predicted data so that the most superior algorithm can be introduced as also was conducted in this article. Such an algorithm enables more optimized purchase suggestions for new and potential customers. In this way, customers with little or no purchase interest can also be encouraged to use the fintech-applying companies and their applications to make purchases.

2. The model proposed in this research paper has been drawn on the data of a downsized sample. The main study's sample was a lot larger and included all the customers from the previous years. After recognizing the various sets of customers, the information banks can be upgraded (such as by eliminating the deceased customers and adding the newly found customers) to take measures for making the sporadic customers more loyal through such ways as reestablishing communication with the forsaken customers, identification of the customers with a high number of transactions during several years and so forth thereby to make more effective interventions for rendering all the customers loyal.

3. Creation of a larger and more comprehensive model that can include clusters of some extra personal information like customers' education levels, jobs, ages and so forth for the subsequent offering of person-specific services following an investigation of the model's prediction error and accuracy rates in line with rendering customers more loyal.

B) Research Suggestions (to the Future Researchers):

1. Considering the present research's findings that have been obtained as outputs of the DNN optimization algorithm, it can be proposed that this algorithm should be trained by new datasets of the other fintech-applying companies.

2. DNN optimization method, evidenced herein as the algorithm with the lowest error and highest accuracy of prediction, can be utilized in comparative studies about the customers' use of applications introduced by the fintech-applying companies. The results can be compared with the findings of the foreign research, and a more all-inclusive algorithm can be consequently achieved within the framework of the future and further studies.

References

[1] O. Acar and Y.E. Çıtak, *Fintech integration process suggestion for banks*, Procedia Comput. Sci. **158** (2019), 971–978.

[2] H. Baber, *Impact of FinTech on customer retention in Islamic banks of Malaysia*, Int. J. Bus. Syst. Res. **14** (2020), no. 2, 217–227.

[3] C.M. Barbu, D.L. Florea, D.C. Dabija and M.C.R. Barbu, *Customer experience in fintech*, J. Theor. Appl. Electron. Commerce Res. **16** (2021), no. 5, 1415–1433.

[4] B. Brandl and L. Hornuf, *Where did fintechs come from, and where do they go? The transformation of the financial industry in Germany after digitalization*, Front. Artif. Intell. **3** (2020), no. 8.

[5] R.P. Buckley and S. Webster, *FinTech in developing countries: charting new customer journeys*, J. Financ. Transform. **44** (2016).

[6] S. Carbó-Valverde, P.J. Cuadros-Solas and F. Rodríguez-Fernández, *Entrepreneurial, institutional and financial strategies for FinTech profitability*, Financ. Innov. **8** (2022), no. 1, 1–36.

[7] A. Chhaidar, M. Abdelhedi and I. Abdelkafi, *The effect of financial technology investment level on European banks' profitability*, J. Knowledge Econ. (2022) 1–23.

[8] T. Cojoianu, G.L. Clark, A.G., Hoepner, V. Pazitka and D. Wojcik, *Fin vs. Tech: How does new knowledge creation and lack of trust in financial services incumbents influence the emergence and financing of fintech start-ups?*, Forthcom. Small Bus. Economics, 2019.

[9] D.J. Cumming and A. Schwienbacher, *Fintech venture capital*, Routledge Handbook of FinTech. Routledge, 2021.

[10] S. Darolles, *The rise of fintechs and their regulation*, Financ. Stabil. Review. **20** (2016), 85–92.

[11] M. Fraering and M.S. Minor, *Beyond loyalty: customer satisfaction, loyalty, and fortitude*, J. Serv. Market. **27** (2013), no. 4, 334–344.

[12] J. Frost, *The economic forces driving fintech adoption across countries*, Technol. Revol. Financ. Serv.: How Banks, Fintechs, and customers win together, 2020.

[13] H. Gimpel, D. Rau and M. Röglinger, *Understanding FinTech start-ups–a taxonomy of consumer-oriented service offerings*, Electron. Markets **28** (2018), no. 3, 245–264.

[14] Y. Gov, *Affluent consumer attitude towards brand loyalty worldwide as of March 2017*, Statistica, 2018.

[15] D. Grewal, A.L. Roggeveen and J. Nordfält, *The Future of Retailing*, J. Retail. **93** (2017), no. 1, 1–6.

[16] C.C. Lee, X. Li, C.H. Yu and J. Zhao, *Does fintech innovation improve bank efficiency? Evidence from China's banking industry*, Int. Rev. Econ. Finance **74** (2021), 468–483.

[17] C.I. Mbama and P.O. Ezepue, *Digital banking, customer experience and bank financial performance: UK customers' perceptions*, Int. J. Bank Market. **36** (2018), no. 2, 230–255.

[18] A. Mirchandani, N. Gupta and E. Ndiweni, *Understanding the fintech wave: a search for a theoretical explanation*, Int. J. Econ. Financ. Issues **10** (2020), no. 5.

[19] K. Mustafina and A. Limanskis, *Factors of profitability growth as a sustainability driver in the banking sector*, J. Bus. Manag. **14** (2017).

[20] A. Naimi-Sadigh, T. Asgari and M. Rabiei, *Digital transformation in the value chain disruption of banking services*, J. Knowledge Econ. **13** (2021), no. 2, 1–31.

[21] E. Närvänen, H. Kuusela, H. Paavola and N. Sirola, *A meaning-based framework for customer loyalty*, Int. J. Retail Distrib. Manag. **48** (2020), no. 8, 825–843.

[22] R. Palomo Zurdo, Y. Fernández Torres and M. Gutiérrez Fernández, *Banca cooperativa y transformación digital: hacia un nuevo modelo de relación con sus socios y clientes*, REVESCO. Rev. Estudios Cooperat. **129** (2018), 161–182.

[23] T. Philippon, *On fintech and financial inclusion*, National Bureau of Economic Research, 2019.

[24] F. Pramaswari, A.P. Nasution and S.L.A. Nasution, *The effect of branding quality and service quality on customer satisfaction through Financial Technology (FinTech) at PT WOM finance branch rantauprapat*, Budapest Int. Res. Critics Instit. (BIRCI-Journal) Human. Soc. Sci. **4** (2021), no. 2, 2995–3004.

[25] K. Pousttchi and M. Dehnert, *Exploring the digitalization impact on consumer decision-making in retail banking*, Electronic Markets **28** (2018), no. 3, 265–286.

[26] T. Puschmann and R. Alt, *Sharing economy*, Bus. Inf. Syst. Eng. **58** (2016), 93–99.

[27] I. Ramlall, *FinTech and the financial stability board*, Understand. Financ. Stabil. Emerald Publishing Limited, 2018.

[28] U. Rehman and K.S. Ha, *Factors influencing fintech's customer loyalty for cross Border payments: mediating customer satisfaction*, Asia-Pacific J. Business Ventur. Entrepreneur. **16** (2021), no. 6, 287–297.

[29] M. Siek and A. Sutanto, *Impact analysis of fintech on banking industry*, Int. Conf. Inf. Manag. Technol. (ICIMTech), 2019, pp. 356–361.

[30] M. Soriano, *Factors driving financial inclusion and financial performance in Fintech new ventures : an empirical study*, Working Paper, 2017.

[31] C.T. Tien, H.K. Cheng and S. Pei-Ling, *The mediated effect of relationship marketing on the influences of irritation advertising in fintech times*, In Proc. 2nd Int. Conf. E-Education, E-Business and E-Technology, 2018, pp. 99–101.

[32] A.K. Tripathy and A. Jain, *FinTech adoption: strategy for customer retention*, Strategic Direction **36** (2020), no. 12, 47–49.

[33] N. Vilkaite-Vaitone and I. Skackauskiene, *Service customer loyalty: An evaluation based on loyalty factors*, Sustain. **12** (2020), no. 6.

[34] Z. Yin, Y. Zhao, X. Lu and H. Duan, *Screening of Alzheimer's disease based on multiple neuropsychological rating scales*, Comput. Math. Methods Med. **2015** (2015).