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RESEARCH PAPER

Improving the Omnichannel Customers' Lifetime Value Using Association Rules Data Mining: A Case Study of Agriculture Bank of Iran

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Abstract

Multi-channel marketing causes the customer to lack a unique identity in different channels. This issue overshadows the synergy of the channels in strengthening the positive attitude of the customers. However, an omnichannel marketing strategy can work properly. The main purpose of this study, which was conducted in Agriculture Bank of Iran, was to develop a comprehensive model for calculating customers' lifetime values, analyzing customers' behaviors in different channels by association rules data mining, and analyzing the relationship between omnichannel strategy and CLV. First, the association rules in the big data of customers' banking transactions in different channels were identified using association rules data mining. Then, the CLV indicators were identified and prioritized using interviews, questionnaires, and AHP methods, and the lifetime values of omnichannel and other customers were calculated and compared using t-test. Then, omnichannel customers were categorized based on the association rules and the lifetime values of omnichannel customers of different categories was compared using ANOVA method. Eleven association rules regarding the use of banking channels by omnichannel customers were identified. The results show that there is a significant difference between the lifetime values of omnichannel customers and other customers and the lifetime values of omnichannel customers is 134% more.

Keyword: Omnichannel marketing, Omnichannel banking, CLV, Association rule data mining, Big data.

1. Introduction

In today's competitive markets, where the products and services life cycle and the duration of comparative advantages stability are becoming shorter, focusing on valuable customers and creating a long lasting and valuable communication with them, calculating and improving the customers' lifetime value (CLV) have become increasingly important.

CLV, as the present value of all future profits obtained from a customer over the life of his or her relationship with a firm (Gupta et al., 2006), is very important in developing a marketing strategy, and strategies based on it can lead to increased profitability for a firm (Valenzuela et al., 2014).

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On the other hand, with the advent of new technologies, tremendous changes have taken place in customer service channels. The role of physical retail stores is changing; there is a slight difference between different offline and online channels such as physical stores and exhibitions, web stores, mobile apps, and social media, and the development of new channels crosses old boundaries such as geographical boundaries and customer ignorance (Saghiri et al., 2017). Customer access to various internet and mobile channels and offline or online touchpoints and the widespread acceptance of new technologies have reduced barriers to communication between customers and organizations. These changes are also evident in the banking market, where banks use multiple and different channels such as ATMs, telephone banks, internet banks, mobile bank, etc., to provide services to customers. Diversity, breadth, inconsistency, and lack of integration in different and multiple channels confuse customers in receiving a unique message from communication channels or a product with a unique feature and quality from distribution channels and make it difficult for marketers to predict and guide customer behavior and enhance their lifetime value (Verhoef et al., 2015).

In the meantime, omnichannel marketing strategy has been proposed as a solution to solve these problems. This strategy creates integration between different and multiple communication and distribution channels in order to meet the needs and interests of customers by creating synergy between channels.

On the other hand, the ultimate goal of designing and implementing any business strategy, including omnichannel strategy, depends on how effective it is in attracting, retaining, and meeting customer needs and interests, as well as improving customer lifetime value (CLV). A strategy that does not increase the customer lifetime value cannot lead to the achievement of the company’s mission and goals. This issue and the specific behavior of omnichannel customers in the use of channels have received less attention in previous studies.

Applied studies on omnichannel retail are constantly increasing. Shen et al. (2018) found that 76% of market leaders considered omnichannel strategy as a key priority in business, and that omnichannel management was ranked as the third most important topic in research searches.

Despite various studies on omnichannel marketing, few studies have been done on monitoring and aggregating omnichannel customers’ behaviors in multiple channels and thus calculating their lifetime value. Providing a comprehensive model to identify and calculate customers’ lifetime value, analyzing customer behavior in different channels by association rules data mining (ARDM), and analyzing the relationship between omnichannel strategy and customers’ lifetime value – which has been neglected in previous studies – are the innovations of the present study.

This study, which was conducted as a case study in Agriculture Bank of Iran, seeks to answer the following questions.

1) Does the implementation of omnichannel marketing strategy improve the lifetime value of customers?

2) What is the optimal behavior of omnichannel customers based on the sequence of their use of different banking channels?

So, in this study, first the association rules in customers’ behaviors have been identified using data mining. Then a comprehensive model has been developed to calculate the lifetime value of bank customers, the lifetime value of these customers have been calculated and compared using this model, and the optimal behavior of omnichannel customers, in terms of the sequence of using different channels, has been identified.

Findings of this study can be used by researchers to identify the various dimensions and aspects of omnichannel marketing, develop models for calculating CLV, and identify the relationships between these variables and other variables of marketing science.

In addition, business activists – especially bankers – can use these findings to develop and implement the effective omnichannel marketing strategy and emphasize the channels whose sequence of use helps improve customers' lifetime value in their shopping journey.

2. Literature Review

2.1. Omnichannel

The world of retailing has changed dramatically in the last decade. The advent of online channels and new digital channels such as mobile and social media channels has changed retail business models, retail mix, and buyers' behaviors. With the expansion of various channels, customers buy not only from physical stores or online, but also through various channels. For example, they search and retrieve information from one channel and complete the purchase through another channel (Lee et al., 2019).

Because of these changes in customer behavior, marketing strategies have also changed. In this regard, marketing strategies are divided into single-channel, multichannel, cross-channel, and omnichannel strategies in terms of using limited or multiple channels to communicate or present the product to customers.

Single Channel: The most basic method of communication between businesses and customers is single channel. In this method, customers communicate with the business through only one channel, which is mainly physical communication (e.g., store, bank branch, insurance agency, etc.).

Multichannel: Multichannel marketing is a marketing strategy that uses a combination of consumer interactive channels such as websites, mail order catalogs, direct mail, email, mobile, etc.

In the case of banks, the emergence of channels such as ATMs, telephone banks, Internet banks, mobile banks, etc., has led to the communication of customers with banks in a multichannel manner.

Multichannel studies show that in many cases single channels of multichannel systems still try to operate independently to optimize their output, while consumers prefer to choose their preferred channels based on indicators such as technological factors. As a result, multichannel systems do not create synergy of parallel supply channels (Bhatnagar & Syam, 2014).

In this strategy, with different independent channels, disproportion and instability of production and ordering of information as well as poor inventory efficiency are very likely (Saghiri et al., 2017).

Cross-Channels: This method is more complete than multichannels. In the cross-channel method, each customer has a unique identity that is identified by the same identity in all channels. It should be noted that in the cross-channel method, the communication channels are still independent of each other.

Omnichannel: With the rapid development of in-store technology, multichannel and cross channel services are changing to omnichannel ones. Omnichannel retail refers to a kind of retailing in which, regardless of the channel or stage in which customers are located during the purchase process, the synergetic integration is used to create an integrate brand experience for customers (Cummins et al., 2016). With the integration of different parallel channels, omnichannel services provide customers with an integrated, seamless, and cross-channel shopping experience (Shen et al., 2018).

In such a system, consumers, in their shopping experience, can easily move from one channel to another and thus find their desired product in one channel (for example, on the manufacturer's website), order through another channel (for example, online retailers), and receive the product through another channel (for example, home delivery) (Chopra, 2016; Verhoef et al., 2015).

The findings of previous studies suggest various benefits for retailers and customers, including increased cross-selling channels (Cao & Li, 2015; Gallino & Moreno, 2014), improved operational efficiency and improved customer experience (Gallino & Moreno, 2014), increased customer's loyalty (Van Baal, 2014) and their trust in retailers (Gallino & Moreno, 2014). While increasing the integrity of different channels, it increases operational complexity (Gallino & Moreno, 2014).

Furthermore, by accepting the omnichannel business model, retailers can use a wide range of technologies to track customer behavior, in both physical and virtual environment, gain more comprehensive knowledge about each customer, and better shape their shopping experience (Chen et al., 2018).

In addition, omnichannel helps make the necessary arrangements in the separate service processes and technologies of different channels in order to create a permanent and integrated experience for the customers. The integration quality of the channel and the perceived fluency are the main features of the omnichannel business. The quality of channel integration is an object-based belief because it demonstrates the ability of omnichannel technology to create coherence and integration across parallel channels and reflects customer beliefs about omnichannel technology. Perceived fluency is also a behavioral belief because it refers to how customers evaluate their inter-channel experience that stems from their actual using behavior and reflects their beliefs about using omnichannel technology (Shen et al., 2018).

2.2. Omnichannel Banking

Banks operate in a challenging world with rapid technological changes, while their customers have a perceptual view of technology and their expectations are rising. Such an economic environment requires financial institutions that review their business strategies and activities and make changes to the services they provide to customers. Today, banks are gradually reducing the number of their branches and are designing and implementing processes and systems that are more efficient and effective. Customers' visits to branches are also fading over time; this indicates the need for upgraded and customer-centric processes in self-service channels to increase and improve branch capabilities and customer satisfaction, and ultimately lead to improved profits for financial institutions.

In line with these developments, to gain competitive advantages, banks need to move towards omnichannel banking. Omnichannel banking is different from the current multichannel banking approach in which banks encourage customers to use the cheapest channel. Through channels, omnichannel banking can create a sustainable experience for customers so that they can have seamless visibility of the products and financial services they need. From a customer perspective, the integration advantage of an omnichannel strategy, which of course also exists in omnichannel banking, is to increase the value offered by retailers (Gallino & Moreno, 2014; Gao & Su, 2017).

However, the question is whether the value offered by retailers to customers, which has been increased by adopting an omnichannel strategy, changes the customer lifetime value. In order to answer this fundamental question, the concepts of customer lifetime value (CLV) and association rule must first be explained.

2.3. Customer Lifetime Value (CLV)

Customer Lifetime Value (CLV) is defined as the present value of all future benefits that a company receives from a customer during its lifetime relationship with the company

(Nikkhahan et al., 2011). According to Fishbein and Ajzen's (1975) model, intentions allow individuals to apply all relevant factors that may affect their behavior; in fact, intentions usually predict customer behavior in the best possible way. Intention or conative component is between attitude (CLV stimuli) and behavior (CLV), which is known in relational marketing literature as intentional loyalty (Moliner & Tena, 2016).

Calculating and knowing the CLV enables the company to operate the market segmentation and resource allocation effectively.

There are several models for measuring CLV, including the RFM model. This model is an applied model for CLV that is used in various industries to calculate the customers' lifetime value. In this model, the recency (R), frequency (F), and monetary (M) parameters are used.

Recency: Recency refers to the days after the last purchase, and means that how many days ago was the last customer purchase.

Frequency: Frequency refers to the total number of exchanges with the customer and states that how many times the customer has purchased a service or product from the company.

Monetary: The monetary parameter means the total amount of money paid and shows how much the customer has paid in total transactions with the company (Tarokh & Esmaeili Gookeh, 2019).

2.4. Association Rule Mining

Association Rule Data Mining (ARDM) is one of the most common methods of data mining that can be used to identify attractive knowledge in a large volume of huge given data set. Association rules reflect the interdependence between one subject and another. If there is a connection between several topics, it is possible to predict one of them through other topics. Today, association rules are used in web data mining, recommender systems, intrusion detection, marketing, e-commerce, case analysis, risk management, and other disciplines (Shi et al., 2019). For example, one of the applications of the association rules is their use in the market basket analysis, through which the buying habits of customers are identified by analyzing the products that they place in their shopping baskets. For example, this method can be used with analyzing the products purchased by customers and their sequence over a period of time. Here, it becomes clear that when customers buy product A, how likely it is that they will add product B to their product portfolio.

During the process of rule mining, rule is defined as the form of $A \rightarrow B$ with two restrictions of $A, B \subset I$ and $A \cap B \neq \emptyset$, where I represents the set of items. A is a set of items called antecedent or the left hand side (LHS) and B denotes a set of items referred to as the consequent of the rule or the right hand side (RHS) (Wang et al., 2019).

The degree of the attractiveness of an association rule is indicated by the functions of *support*, *confidence*, and *lift*.

The *support* of an association rule shows the percentage of transactions containing the union of sets A and B, and it is taken to be the probability, expressed as $P(A \cup B)$. *Confidence* is the proportion of the transactions with A that also contain the union of sets A and B. That is expressed as Eq.1 (Wang et al., 2019)

$$Confidence = \frac{Sup(A \cup B)}{Sup(A)} \tag{1}$$

An association rule is considered a valid rule when its *support* is greater than the minimum *support* (ms) threshold defined by the user and its reliability is greater than the minimum *confidence* (mc) threshold defined by the user.

Lift measure is introduced to make up the shortcoming of *confidence* measure that ignores the baseline frequency of the consequent (Eq. 2) (Wang et al., 2019).

$$Lift(A \rightarrow B) = \frac{Sup(A \cup B)}{Sup(A)Sup(B)} \tag{2}$$

If *lift* is equal to 1, then A and B are independent. If *lift* is less than 1, the occurrence of A is negatively correlated with the occurrence of B. A *lift* value more than 1 indicates that the antecedent of a rule positively stimulates the consequent of that rule.

Using the results of ARM in banking, you can understand how much you can expect to use a channel or other channels (such as POS, mobile banking, etc.) when customers use a channel (such as ATM).

3. Research Background

In recent years, several studies have been conducted on the importance of omnichannel marketing, its framework and components, as well as its effects and its relationship with other variables. and the attention of researchers and business activists to this issue is increasing.

According to Shao (2021), although the adoption of an omnichannel strategy is appropriate for traditional retailers (e.g., brick and mortar), this strategy may not be effective for online retailers. In addition, omnichannel retailing does not necessarily lead to lower prices and customer convenience, and ultimately the omnichannel strategy may not be effective for manufacturers. Of course, Wagner et al. (2018) believe that retailers can enhance consumer shopping experiences by providing alternative electronic channels contact points that participate differently in customers' online shopping journeys. On the other hand, Shen et al. (2018) have also pointed out the advantages of omnichannels and believe that the quality of channel integration significantly affects the perceived validity in different channels. They also believe that the impact of perceived validity in the use of omnichannel services is decreased by the experience of internal use and is increased by the experience of external use. Kim and Chun (2018) have done a more complete study on this; they compared the different strategies of the production channels and concluded that if the customers are heterogeneous based on their acceptance of online shopping, the multichannel strategy will be appropriate, and if they are homogeneous, the best strategy is omnichannel.

Many efforts have been made by researchers to design an omnichannel marketing framework and influencing factors. Saghiri et al. (2017) designed a conceptual framework for omnichannel systems, characterized by three dimensions, namely channel stage, channel type, and channel agent. In this framework, integration and visibility have been examined and discussed as the main sponsors that *support* the implementation of the omnichannel framework. Hsia et al. (2020) also point out that omnichannel retailing is still in its infancy, and believe that infrastructure, infrastructure synergy, and individual motivations affect the customer's positional participation in the positive omnichannel retail experience.

Regarding the factors affecting omnichannel and its effects, Hure et al. (2017) believe that there is a significant relationship between offline purchase value and online purchase value with omnichannel purchase value, while no significant relationship is found between mobile purchase value and omnichannel purchase value. Meanwhile, omnichannel power, which is itself a function of the integration and perceptual stability variables, acts as an intermediary variable between the offline purchase value and the omnichannel purchase value. Also Lee et al. (2019) believe that the dimensions of channel quality integration have a positive effect on customer commitment, which leads to the positive word of mouth and positive intentions to buy. With regard to the effects of all channels Herhausen, et al. (2015) believe that channel integration (resulting from a omnichannel strategy) leads to an increase in the perceptual quality of services and a reduction in the perceived risk of online shopping.

Various studies have been conducted on customer lifetime value. The International Data Corporation (IDC) has found that customers who use both online and physical channels have 30 percent more lifetime value than customers who use single channels (online or physical) (Lee et al., 2019). In addition, Suárez and Tejero (2021) have shown that banks make decisions to retain seemingly unprofitable customers based on real options theory and calculating the CLV.

In previous studies, the relationship between omnichannel marketing strategy and other marketing topics such as word of mouth, customer buying intentions, customer commitment, perceptual quality of service, perceptual risk and customer acceptance of online shopping, customer loyalty, sales trust, etc., has been investigated.

On the other hand, the effect of this strategy on other topics of marketing science such as customer lifetime value, customer perceptual value, strengthening the brand equity of the organization, etc., has been less studied. Therefore, in this study, through an emphasis on omnichannel banking customers, the effect of omnichannel marketing on customer lifetime value has been investigated.

The research objectives of this case study on Agriculture Bank of Iran included identifying the behavior of omnichannel customers in terms of the sequence of using banking channels and comparing their lifetime value with each other and with other customers to identify the effect of omnichannel marketing strategy on CLV and identifying the optimal behaviors of omnichannel customers to enhance their CLV. In this regard, the following hypotheses are presented:

> Hypothesis 1): There is a significant difference between omnichannel customers' lifetime value and other customers'.
>
> Hypothesis 2): There is a significant difference between omnichannel customers' lifetime value that have different behaviors.

The reason why Agriculture Bank of Iran has been selected as the research area is that in addition to selecting its target customers from the agricultural, livestock, and food industries in different geographical locations, this bank also emphasizes on financing from other sectors and industries. This diversity in its target market has led to the diversity of its customers, and this has made it necessary to identify the CLV and their classification and plan to improve the CLV of each type of customer classes.

Furthermore, this bank uses various new banking systems such as ATMs, telephone banks, Internet banks, mobile banks, etc., in order to provide banking services to customers. This issue has led to diversity, breadth, and non-integration in banking channels. As a result, it is necessary to pay attention to the omnichannel strategy.

On the other hand, this bank is a state-owned bank and depends on the strategies and policies of higher institutions and organizations in formulating and implementing its marketing strategies and programs; for this reason, less attention has been paid to new marketing principles such as CLV and strategies such as omnichannel marketing.

Therefore, conducting this study can help this bank succeed in a competitive market.

4. Research Methodology

This study is exploratory, applied, and sectional in terms of approach, purpose, and horizon, respectively. It is mixed (qualitative-quantitative) in terms of data collection method; in the qualitative stage, interviews with experts and in the quantitative stage, the survey of real data and a questionnaire were used for data collection.

To achieve research purposes in the quantitative stage, the random sampling method was used to extract a dataset of two-year banking transactions (2018 and 2019) of 138085 customers of Agriculture Bank of Iran, which were performed using different banking channels. Then, using SPSS Clementine 12 software and through the association rule mining method, the rules in the omnichannel customer transaction data set were identified and customers were classified according to the identified rules.

Omnichannel customers are customers who follow the recognized association rules and therefore use different banking channels to receive banking services, e.g., customers who first use ATM, then mobile bank, and finally bank branches to complete the process of receiving their banking services. Naturally, other customers who do not use the identified association rules are non-omnichannel customers.

Next, omnichannel customers who followed association rules were categorized into different groups.

In the qualitative stage, interviews (with 40 experts) and theoretical saturation were used to identify CLV indicators. In addition, to identify the significance coefficients of indicators using AHP method, a questionnaire was designed by researchers for pairwise comparisons of indicators. Then, the reliability and validity of the questionnaire were confirmed using the Kuder-Richardson method and based on the opinions of experts (10 university professors and bank managers) who were selected using random sampling method. The results were used to identify the significance coefficients of the indicators.

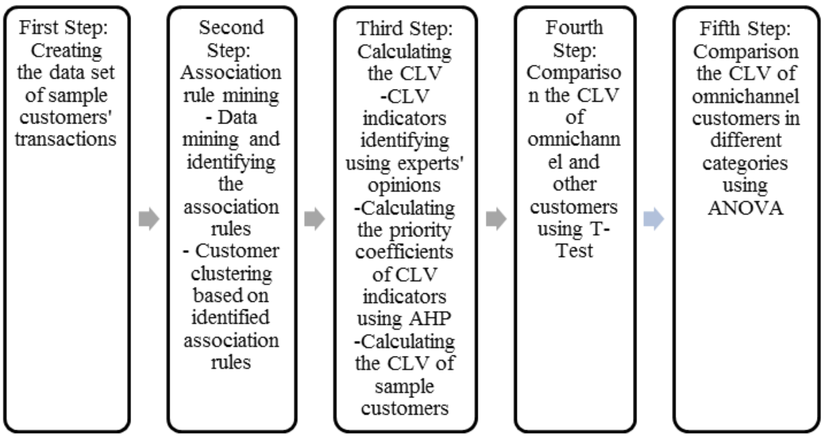
Then, in quantitative step, customers' lifetime value was calculated using the identified indicators (i.e., recency of deposit, deposit consistency, frequency of received services, frequency of depositing, average deposit amount, and average received credit). CLV of omnichannel customers' lifetime value and other customers' were compared using t-test. Subsequently, Omnichannel customers were categorized based on the association rules they follow, and the CLV of omnichannel customers in different categories were compared using ANOVA method and Tamhan test.

It is worth mentioning that the customers' banking transactions data in banks are confidential and customers should be sure about the security of their banking data. Based on this, banking transaction data in this study was provided to researchers anonymously and it was not possible to identify customers related to each banking transaction. Therefore, the principle of fiduciary duty has been observed by banks and researchers.

5. Research Findings

In the following, each of the steps mentioned in Table1 is described and the results are stated.

Table 1. Research Phases



Step 1: Creating the Data Set

The data used in this paper include banking transactions of 138085 customers of Agricultural Bank of Iran in the period of 2018 and 2019. These transactions include depositing and withdrawing bank deposits by customers through various banking channels including POS, ATM, Branch, Internet bank, and Mobile bank.

At the time of writing, the number of active customers of the Agricultural Bank of Iran was 9337999, and according to Morgan's table, the appropriate number of sample participants was 138085.

In creating this data set, random sampling method was used and customers whose bank account was active and who used different banking channels to receive banking services were considered. While some customers have multiple accounts, the bank transactions of these customers in different accounts were analyzed in a consolidated manner. Therefore, in this study, each sample referred to a customer who might have one or several accounts.

Step 2: Association Rule Mining

The data were studied based on the Association Rule Mining method using SPSS Clementine 12 software and the existing rules regarding the sequence of using different channels by these customers were identified.

Then, rules with *support* and *confidence* indicators above 50% (determined by researchers) were considered.

Association rules in the process of using omnichannel customers of Agricultural Bank of Iran were identified. The specifications of these are given in Table 2.

Table 2. Association Rules for Data Mining

RuleID	Antecedent(A)	Consequent(B)	Support%	Confidence%	Lift
1	POS*	ATM**	70.49	95.88	1.171
2	ATM	POS	81.88	82.55	1.171
3	Branch	ATM	63.67	74.03	0.904
4	ATM	Branch	81.88	57.57	0.904
5	POS	Branch	70.49	62.36	0.979
6	Branch	POS	63.67	69.03	0.979
7	POS	ATM and Branch	70.49	60.18	1.277
8	POS and ATM	Branch	67.59	62.76	0.989
9	Branch	POS and ATM	63.67	66.63	0.989
10	POS and Branch	ATM	53.96	96.51	1.179
11	ATM	Mobile Bank	81.88	51.81	1.179

Source: Research findings

*POS (Point of Sale) is a machine that is installed in sales centers and the customer pays his/her purchase price by swiping his/her debit or credit card in it.

**An Automated Teller Machine (ATM) is an electronic banking outlet that allows customers to complete basic transactions without the aid of a branch representative or teller. Anyone with a credit card or debit card can access cash at most ATMs.

In Table 2, *support* is calculated using the equation $P(A \cup B)$, *confidence* is calculated using Eq.1, and *lift* is calculated using Eq.2.

The *lift* indicator in rules 1, 2, 7, 10, and 11 is greater than 1, so the relationship between antecedent and consequent in these rules is a direct relationship.

According to Table 2, based on the association rules, omnichannel customers of Agricultural Bank of Iran have the following characteristics in the process of receiving banking services, in terms of using multiple channels:

1. **Rule 1:** with a probability of 95.88%, customers who use the POS channel will also use the ATM channel.

2. **Rule 2:** with a probability of 82.55%, customers who use the ATM channel will also use the POS channel.
3. **Rule 7:** with a probability of 60.18%, customers who use the POS channel will also use the ATM and Branch channels.
4. **Rule 10:** with a probability of 96.51%, customers who use the POS and Branch channels will also use the ATM channel.
5. **Rule 11:** with a probability of 51.81%, customers who use the ATM channel will also use the mobile bank channel.

The *lift* index in rules 3, 4, 5, 6, 8, and 9 is less than 1; therefore, the relationship between antecedent and consequent in these rules is an inverse relationship:

6. **Rule 3:** with a probability of 74.03%, customers who receive banking services from the Branch channel will not use the ATM channel.
7. **Rule 4:** with a probability of 57.57%, customers who use the ATM will not use the Branch channel.
8. **Rule 5:** with a probability of 62.36%, customers who use the POS channel will not use the Branch channel.
9. **Rule 6:** with a probability of 69.03%, customers who receive banking services from the Branch channel will not use the POS channel.
10. **Rule 8:** with a probability of 62.76%, customers who use the POS and ATM channels will not use the Branch channel.
11. **Rule 9:** with a probability of 66.63%, customers who use Branch channel will not use POS and ATM channels at the same time.

After identifying the mentioned rules, the sample customers who followed the identified rules and showed the rules in their purchase behavior were categorized in 11 groups (as Table 3 shows). However, in the next steps, only categories with *lift* indicator values larger than 1 and direct antecedent-consequent relationship (i.e., classes 1, 2, 7, 10, and 11) were considered:

Table 3. Customer Classes

Rules ID	1	2	3	4	5	6	7	8	9	10	11
Categories	1	2	3	4	5	6	7	8	9	10	11
number of customers per category	3401	3951	3072	3951	3401	3072	3401	3261	3072	2121	3951

Source: Research findings

Customer clustering based on identified rules allows customers who have similar behavior in terms of usage and sequence of channel usage to be placed on the same cluster. Clustering customers based on their actual behavior will make the results of the analysis more valid.

Step 3: Calculating the CLV

In order to use the results of the Association Rules Mining in effective omnichannel marketing planning, it is necessary to consider the impact of the identified rules on CLV improvement. For this purpose, first, it was necessary to identify the CLV indicators of Agricultural Bank of Iran customers and then determine the coefficients of importance of each of them. For this purpose, a portfolio of CLV calculation indicators was identified based on interviews with experts (Agricultural Bank of Iran managers, including 20 heads of branches, 14 deputies of general departments, and 6 heads of general departments) and saturated sampling method.

In order to conduct pairwise comparison and to analyze and identify the coefficients of importance of the indicators using AHP method, a questionnaire was prepared by researchers. The reliability of the questionnaire was examined using Kuder-Richardson model, and based on the obtained reliability coefficient (0.72), the reliability of the questionnaire was approved. The validity of the questionnaire was also confirmed by experts (a number of university professors and bank managers). The decision hierarchy tree of CLV calculation indicators is as Figure 1.

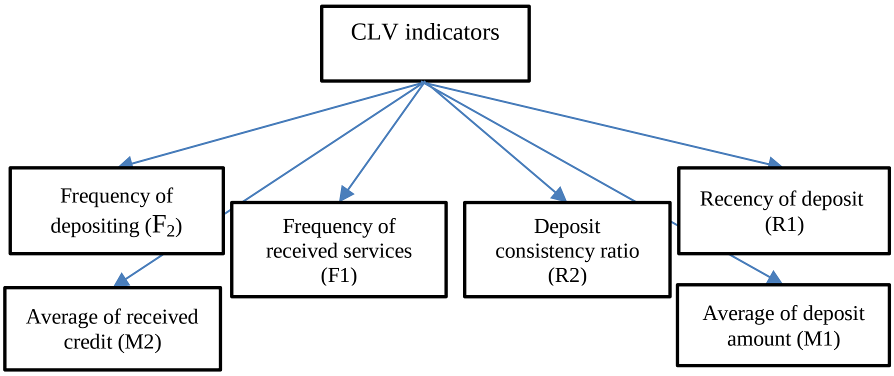


Figure 1. Hierarchical Decision Tree of AHP Model (Source: Research Findings)

Then, 330 managers of the Agricultural Bank of Iran (including 45 heads of departments, 75 deputies of departments, and 210 heads of branches) were selected as samples based on stratified random sampling and their opinions on the comparison of the importance of CLV indicators were collected using a questionnaire. Given that the number of managers of the Agricultural Bank of Iran, as a target community, is equal to 2098 people, according to Morgan’s table, the sample size was reasonable.

In order to use the AHP model to analyze the collected data, the pairwise consistency rate was first measured. These calculations showed that the consistency rate was 0.07 and acceptable (less than 0.1). After that, the geometric mean of the respondents’ opinions about the questionnaire was calculated and in this way, their opinions were combined. Then, to determine the priority coefficient of each indicator, first the integrated matrix was normalized by dividing each of the combined matrix processes on the total column, and then using the geometric mean of each of the normalized matrix lines, the priority coefficient was identified. Finally, by dividing each of the coefficients by the sum of the priority coefficients of the indicators, the calculated coefficients were normalized. Figure 5 shows the average values of normal pairwise comparisons and the priority coefficients of the indicators.

The normalized matrix and the normalized priority coefficients CLV indicators are listed in Table 4.

Table 4. The Average of the Normalized Pairwise Comparisons and the Priority Coefficients of the Indicators

	(R_1)	**(R_2)**	**(F_1)**	**(F_2)**	**(M_1)**	**(M_2)**	**Geometric Mean**	**Normalized Priority (W_i) Coefficients**
(R_1) Recency of deposit	0.06	0.15	0.18	0.01	0.07	0.21	0.08	0.09
(R_2) Deposit consistency ratio	0.02	0.05	0.18	0.09	0.09	0.21	0.08	0.09
(F_1) Frequency of received services	0.01	0.01	0.04	0.02	0.07	0.04	0.02	0.03
(F_2) Frequency of deposit	0.39	0.34	0.26	0.09	0.08	0.13	0.18	0.20
(M_1)Average of received credit	0.51	0.44	0.33	0.78	0.62	0.38	0.49	0.56
(M_2) Average of deposit rate	0.01	0.01	0.01	0.02	0.07	0.04	0.02	0.02

Source: Research findings

Finally, the formula for calculating CLV, which is derived from the RFM model, was designed as Eq. 3:

$$CLV=w_1R_1 + w_2R_2 + w_3F_1+ w_4F_2+ w_5M_1+w_6M_2 \quad (3)$$

w_1, w_2, w_3, w_4, w_5, w_6: in order, priority coefficients recency of deposit (R_1), deposit consistency (R_2), frequency of received services (F_1), frequency of depositing (F_2), average of deposit amount (M_1), and the average of received credit (M_2) which are equal to the W_i column in Table 4. Therefore, the CLV formula of the Agricultural Bank of Iran customers is equal to Eq. 4:

$$CLV=0.09R_1 + 0.09R_2 + 0.03F_1+ 0.2F_2+ 0.56M_1+0.02M_2 \quad (4)$$

Then, the CLV of the sample customers was calculated using the above formula and based on the information in the dataset transaction of the customers.

Step 4: Comparison of the CLV of Omnichannel and Other Customers

Here, omnichannel customers were customers who used the banking channels based on the association rules identified in Figure 6, and their *lift* indicator was greater than 1, i.e., the customers of categories no. 1, 2, 7, 10 and 11, which are categorized in group 1 in Table 5. Other customers are customers whose use of different banking channels does not have a specific association rule; these customers are categorized in group 2. This group included customers who were in dataset, but during the time considered (2018 and 2019) did not use any banking channels have not been considered; the number of these customers is 105,181.

To compare the CLV of these two groups, t-test was used. H_0 and H_1 of this test would be as Eq. 5:

$$\begin{aligned} &H_0: \mu_1= \mu_2 \\ &H_1: \mu_1\neq \mu_2 \\ &\mu_1\text{: CLV average of omnichannel customers} \\ &\mu_2\text{: CLV average of other customers} \end{aligned} \quad (5)$$

The outputs of SPSS 22 for t-test are showed in Table 5 and 6.

Table 5. T-Test Results

Group statistics					
	Groups	**N**	**Mean**	**Std. Deviation**	**Std. Error Mean**
CLV	1	11738	301.74	15.88	.146
	2	21166	128.42	90.59	.622

Resource: Research findings

The number of omnichannel customers (group 1) is 11738, their CLV average is 301.74, and their standard deviation is 15.88. The number of other customers (group 2) is 21166, their CLV average is 128.42, and their standard deviation is 90.59.

Table 6. Independent Samples Test

		Levene's test for equality of variances		t-test for equality of means						
		f	sig.	t	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% confidence interval of the difference: Lower	Upper
CLV	Equal variances assumed	79738	.706	205	32902	.006	173.31	.84	171.66	174.96
	Equal variances not assumed			270	23446	.006	173.31	.63	172.06	174.56

Source: Research findings

In Table 6, since the significance value is greater than 0.05, the assumption of the equivalence of variances is accepted and first-line data are used to interpret the table content. Since the test is two-tailed and the significance value of the first row is equal to 0.006, the H_0 – which shows that the average CLV of the two groups is equal – is not acceptable at 0.95 confidence level.

Therefore, based on the analysis of Table 6, research hypothesis 1 is confirmed, and we might maintain with 95% confidence that there is a significant difference between Agricultural Bank or Iran omnichannel customers' lifetime value and those of its other customers. Based on the findings, the amount of this difference is equal to 173.31 (134%).

Step 5: Comparison of the CLV of Omnichannel Customers

In the fifth step, using SPSS 22 software, the average CLVs of omnichannel customers were compared and their differences were examined, as shown in Table 7.

Table 7. ANOVA Results

	Sum of Squares	df	Mean Square	F	Sig.
Between groups	345502	4	86375	387	.000
Within groups	2615693.07	11733	222		
Total	2961195	11737			

Source: Research findings

The significance value shown in Table 7 is 0.000. Therefore, hypothesis 2 is confirmed, and we might maintain with 95% confidence that there is a significant difference between omnichannel customers' lifetime values that have different behaviors.

Having different behaviors mean they follow the different association rules identified in the use of different banking channels.

Then, in order to achieve the research purposes and identify the optimal behavior (following the optimal association rules) of omnichannel customers to improve the customers' lifetime values, the average CLV of omnichannel customers were compared.

Selecting the test type to compare the average CLV of omnichannel customers in different categories depends on the result of variance homogeneity test. In this study, Levene's test was used for this purpose.

Table 8. Test of Homogeneity of Variances

Levene statistic	df1	df2	Sig.
296	4	11733	.000

Source: Research findings

Based on Table 8, because significance is less than 0.05, it can be concluded that there is a significant difference among the variance of CLVs of omnichannel customers in different categories; therefore, the Tamhane's test, in which the variance of the groups is assumed heterogeneous, was used to compare the average CLVs of omnichannel customers in different categories.

Table 9. Multiple Comparisons Between Categories Based on CLV

Category(I)	Category(J)	Mean difference (I-J)	Std. error	Sig.	95% Confidence interval	
					Lower bound	Upper bound
1	2	2.82*	.14	.000	2.40	3.23
	7	6.23*	.28	.000	5.45	7.02
	10	-3.08*	.80	.001	-5.32	-.84
	11	-16.42*	.40	.000	-17.57	-15.28
2	1	-2.82*	.14	.000	-3.23	-2.40
	7	3.41*	.29	.000	2.58	4.24
	10	-5.90*	.80	.000	-8.16	-3.64
	11	-19.25*	.41	.000	-20.42	-18.07
7	1	-6.23*	.28	.000	-7.024	-5.45
	2	-3.41*	.29	.000	-4.24	-2.58
	10	-9.32*	.84	.000	-11.67	-6.96
	11	-22.66*	.48	.000	-24.01	-21.31
10	1	3.08*	.80	.001	.84	5.32
	2	5.90*	.80	.000	3.64	8.16
	7	9.32*	.84	.000	6.96	11.67
	11	-13.34*	.89	.000	-15.84	-10.84
11	1	16.42*	.40	.000	15.28	17.57
	2	19.25*	.41	.000	18.07	20.42
	7	22.66*	.48	.000	21.31	24.01
	10	13.34*	.89	.000	10.84	15.84

Source: Research finding *. The mean difference is significant at the 0.05 level.

Table 10. Descriptive Table of Comparisons Between Different Categories

CLV Descriptive

Categories	Antecedent	Consequent	N	Mean	Std. deviation	Std. error	95% confidence interval for mean		Minimum	Maximu
							Lower bound	Upper bound		
1.0	POS	ATM	3140	302.02	4.53	.081	301.87	302.18	300	344.98
2.0	ATM	POS	4298	299.20	8.15	.12	298.96	299.45	100	300
7.0	POS	ATM and Branch	1700	295.79	11.07	.26	295.26	296.31	215.09	300
10.0	POS and Branch	ATM	1750	305.11	33.31	.79	303.55	306.67	9.35	318
11.0	ATM	Mobile bank	850	318.45	11.68	.40	317.67	319.24	300	337.31
Total			11738	301.74	15.88	.14	301.45	302.02	9.35	344.98

Source: Research findings

Based on the results presented in tables 9 and 10, which are the result of the Tamhane test, we might maintain with 95% confidence that there is a significant difference among the omnichannel customers' lifetime value in different categories and their average CLVs. The values (ordered from more to less) in categories 11, 10, 1, 2, and 7 are equal to 318.45, 305.11, 302.02, 299.20, and 295.79, respectively.

The differences among the average CLVs of omnichannel customers in different categories are shown in Table 11.

Table11. Comparison the CLV of Omnichannel Customers in Different Categories

	Categories	1	2	7	10	11
		Pos→ATM	ATM→Pos	Pos→ATM & Branch	Pos & Branch→ATM	ATM→MobileBank
1	Pos→ATM		2.82	6.23	-3.08	-16.42
2	ATM→Pos	-2.82		3.41	-5.90	-19.25
7	Pos→ATM & Branch	-6.23	-3.41		-9.32	-22.66
10	Pos &Branch→ATM	3.08	5.90	9.32		-13.34
11	ATM→MobileBank	16.42	19.25	22.66	13.34	

Source: Research findings

6. Discussion and Conclusions

In today's competitive market, where the life cycle of products and services and the sustainability of companies' relative benefits are shortened, it is not possible to succeed without studying customer behavior and developing strategies to enhance their lifetime values. Delivering banking services through numerous and diverse channels, developing an omnichannel strategy, and coordinating and integrating the different channels have made it more necessary to shape customers' behavior and enhance their lifetime values.

Studying the big data of how to use banking services and identifying the association rules in the behavior of banking customers can be effective in implementing the omnichannel strategy and integrating between banking services and channels.

In a study by Aggelis (2004) the way of discovery of association rules between different types of e-banking payment offered by a bank is described along with experimental results. The basic outcome is that value added tax (VAT) payment orders and social insurance institute (SII) payment orders are the most popular and interconnected strongly. Kargari & Eshraghi (2018) studied the fraud behavior in banking service using association rule data mining; Findings suggest that the employment of both rule-based and clustering-based components leads to the detection of more frauds while fewer alarms will go off.

In these studies, or similar studies that have been reviewed in this paper, the association rules of consumer behavior in receiving banking services have been studied and the channels of providing these services have not been examined. While this paper examines the association rules of using banking channels, using data mining.

In the present study, which was conducted as a case study in the banking industry on the Agriculture Bank of Iran, first the current behaviors of sample customers of the Agricultural Bank of Iran in using different banking channels were identified through the Association Rule Data Mining method. A summary of results provided in the previous section of this article is shown in Figure 2.

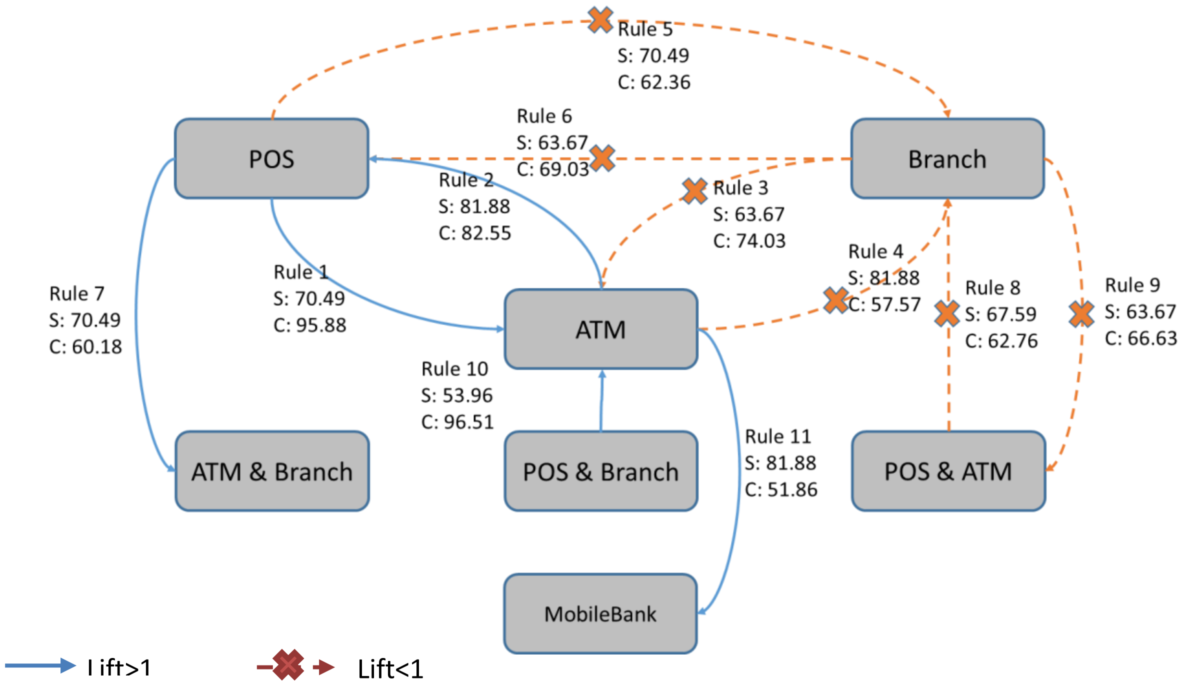


Figure 2. Diagram of Association Rules Mining Result (Source: Research Finding)

In association rules with a *lift* greater than 1, i.e., rules in which the relationship between antecedent and consequent is direct, POS plays a key role. These association rules, with different probabilities, indicate that customers who use POS will also use ATM and customers who use ATM will also use POS. Customers who use ATM tend to use Mobile Bank. Customers using POS tend to use ATM and Branch at the same time. Customers who use POS and Branch simultaneously also tend to use ATMs.

Among the association rules whose *lift* is less than 1, i.e., rules in which the relationship between antecedent and consequent is inverse, the use of Branch plays a special role, so that, customers who use bank branches don't tend to use ATM, POS, and POS & ATM (simultaneously). In addition, customers who use POS or ATM or POS & ATM (simultaneously) will not be willing to use Branch.

These association rules can be the basis of omnichannel marketing, so the channels of these association rules should be integrated and omnichannel customers should be directed to these integrated channels.

Then, sample customers were categorized based on the use of identified association rules.

In order to calculate the CLV of Agricultural Bank of Iran customers, first the indicators measuring CLV and their priority coefficients were identified based on the opinion of bank experts and using AHP method.

Recency of deposit, deposit consistency, frequency of received services, frequency of depositing, average deposit amount, and average of received credit were the main indicators of Agricultural Bank customers' lifetime value. Due to the similarity of banking services and customers of banks in Iran, these indicators can be generalized to other banks.

Among these indicators, recency of deposit and average of deposit amount are more important than others; accordingly, banks should try to strengthen these indicators to improve their customers' lifetime value.

In the next step, the CLV of customers was calculated using identified indicators and two-year (2018 and 2019) history of sample customers' banking transactions.

Subsequently, the CLV average of omnichannel customers (customers who follow identified association rules) and other customers was compared using t-test. The results showed that with 95% confidence, the difference between the omnichannel customers' lifetime value and the other customers' was significant and the CLV average of omnichannel customers was 2.34 times of the CLV of other customers. So, Hypothesis 1 was confirmed.

The priority of association rules identified in omnichannel marketing management required comparing the CLV average of omnichannel customers, who use different association rules. Therefore, first, the sample customers were categorized based on the identified association rules, and the difference between the omnichannel customers' lifetime value were examined using ANOVA method as well as Tamhane method. The results showed that with 95% confidence, the difference between CLV of omichannel customers of different categories was significant (Hypothesis 2 was confirmed) and the average CLV of omnichannel customers of the Agricultural Bank of Iran (ordered from more to less) in categories 11 (ATM → MobileBank), 10 (POS & Branch → ATM), 1 (POS → ATM), 2 (ATM → POS) and 7 (POS → ATM & Branch) were 305.11, 318.45, 302.02, 299.20, and 295.79, respectively. Table 11 showed the differences between the average CLV of omnichannel customers of different categories.

Based on these findings, the implementation of omnichannel strategy enhances customers' lifetime value and omnichannel customers' lifetime value is more than others.' This highlights the importance of an omnichannel marketing strategy in enhancing customers' lifetime value.

On the other hand, the behavior of omnichannel customers differs significantly based on the sequence of the use of channels, and the CLV of customers who use the 11, 10 and 1 association rules have the highest CLV. Therefore, in developing an omnichannel strategy, special emphasis should be placed on these association rules.

7. Suggestions

The above results indicate that in the competitive market of banking services, where banks have offered several electronic banking channels to provide services and customers' knowledge has been upgraded to use electronic banking channels, adopting a omnichannel marketing strategy to expand visibility to channels and create integration between them can lead to increased customer lifetime value (CLV). Therefore, the following points are suggested.

1. **Identify customer association rules through a data warehousing system:** Changes in customer behavior are becoming faster day by day, so the identification of association rules in the behavior of omnichannel customers should be done continuously. It is therefore recommended to the Agricultural Bank of Iran to develop and use systems such as data warehouse to analyze customer behavior, discover and categorize customer needs and interests, and use the results to personalize services, which is one of the goals of omnichannel marketing.

2. Develop banking channels based on effective association rules: In order to improve its omnichannel customers' lifetime value, the Agricultural Bank of Iran should develop their access to POS, ATM, and mobile banking channels, which are emphasized in the recognized association rules; the use of ATM channels will encourage customers to use other electronic banking channels and reduce the use of the branches.

3. Reengineer the process of banking services based on effective association rules: The process of providing banking services to customers might be designed in such a way that there is communication and integration between different channels based on the findings of association rule mining, and customers can access the history and results of services when using different channels and can continue the process of receiving services from one channel to another. For example, it is suggested that the transaction history of the customers in any channel can be accessed on the others, or that it can be possible in mobile bank for customers to verify transactions such as the payment of checks issued by them and the payment required to their verification.

4. Homogenize the channels: Different channels, which are in sequence according to the identified association rules, should be homogeneous in terms of content, color, design, usability, usability, and process;

This homogeneity can lead to the homogeneity of customers' perceptions about different channels, which is one of the important goals of omnichannel marketing.

Theoretically, in order to conduct future studies, the following points are suggested.

1. Develop a comprehensive model: In studies on omnichannel marketing, the various features, dimensions, and structures of omnichannel marketing have been studied separately and a comprehensive model has not been designed so far. However, success in designing an effective omnichannel strategy requires a comprehensive understanding of the various dimensions of the omnichannel concept. It is then suggested that the identification of different dimensions of omnichannels and the design of a comprehensive model for it be considered in future research.

2. Conduct an interdisciplinary study: Studies on the omnichannel strategy can be divided into two areas, namely information technology and marketing. Studies in the field of information technology have dealt only with the hardware and software dimensions, and studies in the field of marketing have dealt only with the communication, advertising, sales, and distribution dimensions.

The successful development and implementation of an omnichannel strategy requires coordination between these disciplines, which can be considered in future research with a team of IT, marketing, and banking researchers.

3. Conduct this study in other industries: The present study has been conducted in the banking industry and specifically in the Agriculture Bank of Iran. It is suggested that this research might be done in other industries as well.

8. Limitations

Researchers faced some limitations in conducting this research, including what follows.

1. Conducting this research using data mining method required access to real data of customers' banking transactions and identification of their behavior. Due to the confidentiality of customers' banking transactions, this access was difficult and coded and without the possibility of identifying customers, while access to some customer demographics could increase the validity of the research findings.

2. Considering that this research has been conducted in the banking industry and specifically as a case study in the Agricultural Bank of Iran, the results are less generalizable to other industries. Of course, the results can be used to conduct research in other industries.

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