Extending Loyalty Programs with BI Functionalities A Case Study for Brick-and-Mortar Stores

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Abstract

Effective customer loyalty programs are essential for every company. Small and medium sized brick-and-mortar stores, such as bakeries, butcher and flower shops, often share a common overarching loyalty program, organized by a third-party provider. Furthermore, these small shops have limited resources and often cannot afford complex BI tools. Out of these reasons we investigated how traditional brick-and-mortar stores can benefit from an expansion of service functionalities of a loyalty card provider. To answer this question, we cooperated with a cross-industry customer loyalty program in a polycentric region. The loyalty program was transformed from simple card-based solution to a mobile app for customers and a web-application for shop owners. The new solution offers additional BI services for performing data analytics and strengthening the position of brick-and-mortar stores. Participating shops can work together in order to increase sales and align marketing campaigns. Therefore, shopping data from 12 years, 55 shops, and 19,000 customers was analyzed.

1. Introduction

Customer loyalty programs are essential for every selling or trading institution [6, 10, 14, 22]. Collecting data about customers and their preferences enables the creation of tailored products and services. In times of multi-channel sales, the competition of offline versus online retailers, and rivalry between products and services, it is costly and hard to maintain customer loyalty [6, 19, 30]. Loyalty programs aim at establishing a trustful customer-company relationship. However, the customer needs to be well understood, to ensure the effectiveness of such programs [31]. Consequently, data-driven customer relationship management increases in importance. Another important aspect is the digitalization of customer loyalty programs with extended functionalities [9]. This translates in replacing physical loyalty cards with online and mobile solutions. Digital solutions provide a variety of new possibilities, such as improved information exchange between the loyalty system and the customer [9].

Current research on customer loyalty focuses mainly on customer shopping behavior, behavioral change and manipulation, reward strategies, and the design of loyalty programs [8, 10, 19]. While the business impact of loyalty programs and data mining techniques in general are researched extensively [22, 26], there has been little publications on real world case studies, combining such loyalty programs with additional Business Intelligence (BI) functionalities for cross industrial small brick-and-mortar shops.

The overarching idea of our research study is to offer small and medium sized stores, within a common loyalty program, additional BI services. This leads us to the research question: “How can small brick-and-mortar stores benefit from the expansion of the service of customer loyalty programs?”. Especially single bakeries, farmer-, flower-, butcher-, and souvenir shops face limited resources. They cannot invest extensively in own BI tools, as set-up and operations costs are very high. Furthermore, they lack the necessary time and capabilities to host and deploy sophisticated BI tools [25]. For these small brick-and-mortar stores, an overarching planning system embedded in the customer loyalty program can be a valuable alternative to address these concerns. For example, new possibilities and a closer collaboration between loyalty programs and shops can be established. Moreover, small shops have the possibility to improve their workforce and sales planning strategies, as well as to better understand customer behavior and habits.

This research paper presents a case study in which an existing card-based loyalty program was transformed to a mobile app for the customer and a web application for the shop owners. Additionally, strategies of how to create value from existing customer data are discussed. Therefore, the data from about 12 years, 19,000

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customers, and 55 shops has been analyzed and illustrated.

The paper is organized accordingly. The next chapter provides an overview of existing research. The third chapter introduces the use case, including the main characteristics of the loyalty program. Then the results of the data analysis are presented, along with the introduction of the expanded functionalities of the transformed loyalty program. Afterwards, ideas about strengthening the collaboration between stores in a cross industrial setting are discussed. Based on this, participating shops can collaborate in order to reinforce sales and strengthen certain shopping locations. Furthermore, the dependency between currency rate and shopping behavior is illustrated. At the end the main findings are summarized.

2. Related work

2.1. Customer loyalty

Customer loyalty is defined as the result of an enduring business relationship [18, 19]. Resulting from this relationship, customers show repeated buying behavior. The enduring business relationship cannot be established directly but is based on customer's satisfaction and trust as two underlying concepts [14]. Different types of loyalty are defined in the literature, namely true loyalty, latent loyalty, spurious loyalty and low loyalty [8]. These concepts include two dimensions, the repeated buying behavior and the emotional attitude towards the brand and product. Tightly linked to the emotional attitude is the role of regret [7]. Each purchase is evaluated posteriori and either creates positive feelings towards the product when the customer's needs are fulfilled or regret feelings when the customer's needs are not satisfied. These emotions influence the prospective purchase decision of the customer.

2.2. Loyalty programs

Effective loyalty management becomes increasingly important, especially when customers are not bound to a contract or face insignificant switching costs [27]. Therefore, loyalty programs aim at building a close relationship with the customer by analyzing their preferences and needs. The market share of loyalty programs has increased over time so that 90% of the people in North America and in Europe are members in at least one loyalty program [10]. The rewards and incentives offered by the loyalty program strongly influence customers' behavior towards using the program [18]. Not only the quantity of a reward, but also the timing is important to maintain or increase loyalty [18, 19]. Furthermore, the customer's generation is changing from X to Y including a change of values and culture, resulting in customers preferring direct rewards and individual treatment [6]. These customers are strongly influenced by online reviews of their peer group [8]. Cedrola and Memmo [10] claim that customers are more loyal when they own a single loyalty card from one provider. Several loyalty programs in the same industry decrease the relationship to the customer. To conclude, many studies focus on large enterprises implementing or managing loyalty programs [9, 10, 17].

2.3. Data mining and value creation process of data analytics

2.3.1. Business Intelligence. BI systems aim at supporting decision making within an organization. Through the integration of internal and external data, insights into market potential, sales position and predictions can be generated [15]. There are different maturity levels of BI systems reaching from spreadsheet solutions up to knowledge management applications including active process management with data mining and real-time analysis [13, 15]. In order to adapt to business changes, BI systems need to be designed in a flexible manner and need to allow the expansion of services [24]. While BI systems have been successfully implemented in large enterprises, small and medium sized enterprises struggle to adopt and implement BI systems [25]. Nevertheless, Olszak et al. [25] claim that BI tools are extremely important for small and medium enterprises and that such systems lead to a competitive advantage.

2.3.2. Shopping basket analysis. Association rule mining was introduced by Agrawal et al. in 1993 [2, 3]. The goal is to extract knowledge from database transactions, more specifically out of itemset (items purchased together) [3]. Generated rules are describing relations between items, where an itemset X is an antecedent and itemset y is a consequence. With the association rule mining, it becomes possible to derive knowledge from products that are purchased together. Knowing the consequence of an antecedent product bundle is helping to establish cross or up-selling. Different measures are calculated, namely support, lift and confidence [2, 3].

2.3.3. Single Value Decomposition. The single value decomposition (SVD) is a technique used for dimensionality reduction.

$$M = U * \Sigma * V^T$$

Formula 1: Single Value Decomposition

Previous unknown latent concepts are derived by splitting an input matrix M. M has the shape of m*n. The input matrix m is then decomposed into U, Σ, V, where U has the dimensions m*m, Σ m*n and V* n*n [28]. The single value decomposition of matrices is used in recommender engines to reduce the complexity of the recommendation problem [4, 23]. Also, it is applied in the topic modeling algorithm Latent Semantic Analysis (LSA) where a text-word matrix from a bag-of-words model is decomposed into U, a text-to-concepts and V, a concept-to-word matrix [12]. Therefore, SVD is applicable to different applications, such as text mining or product recommendation tasks.

2.3.4. Customer Lifetime Value Prediction. Another important concept in customer relationship management is the customer lifetime value (CLV). It measures the economic value of a customer for the company over time [5, 16]. The Recency, Frequency and Monetary Value (RFM) measurement is used to estimate the CLV. The RFM measures the frequency and money spend per customer and the time elapsed since the last purchase, in order to estimate the value of this customer for the company [1, 16, 21, 29].

3. Use Case

This research examines the potential of an extended customer loyalty program and shares the implications of a case study. Data has been collected in over two years of project involvement, through interviews with customers and shop owners, project leaders and the respective ministry of finance. Several projects have been executed, including business model development, extension of BI functionalities to strengthen the local brick-and-mortar stores, and extensive data analysis, summarized in this research paper. The loyalty program is active for over 14 years, as a card-based system. The program is focusing on brick-and-mortar shops in a polycentric region with multiple currencies and e-commerce as multiple external influences.

Two major issues were identified, making the reengineering of the customer loyalty card necessary:

1) Inefficient processes and high administration effort with the outdated system
2) Dissatisfaction with the functionalities and efficiency of the outdated loyalty card program

The outdated card-based system is characterized by a card reader installed in every store. The card readers were outdated and not connected to a common database. Instead, a manual readout was performed in fixed intervals in all shops. Furthermore, the card readers were fragile, and data were stored in the internal memory until the next manual read out. Over the years several data losses occurred. Interviews conducted with the shop owners indicated dissatisfaction with the loyalty program in place, due to a lack of functionalities and no noticeable effect on sales and customer loyalty.

3.1. Available data

Since the loyalty program is in place for 14 years, a lot of data have been collected. Shopping data from 55 shops, 19,000 customers and 12 years are available. The data contain customer details, transactions, and shops, listed in separate tables. Each transaction is linked to the customer details and shop where the purchase was made. In order to enrich the dataset, the weekday was derived from the timestamp (Figure 1). Furthermore, the shops were categorized into industry branches.

Figure 1: Available data and structure

In order to respect data privacy, individual customer details were deleted and excluded from the analysis. Unfortunately, over the last years, data about purchased products were not stored in the loyalty program. The reason is that many of the participating small brick-and-mortar stores had no electronic data warehousing or advanced electronic cash systems for capturing this information.

3.2. Main characteristics of the loyalty program

- 55 shops across various industry sectors participate, such as bakeries, flower, butchery, souvenir and paper shops.
- The loyalty program is operating in a multi-border location. However, is just available in one country.
- Products and services are more expensive than in neighboring countries.
- Most shops have between 2 and 20 employees.
- Data from over 12 years available.
- 19.000 registered loyalty cards.
- 1.6 million transactions.

- The loyalty program is free of charge for the customer.
- Shop owners need to pay a monthly fee. In addition, 1.2% of the purchased amount per customer is transferred to the loyalty program.
  - The customer receives a reward of 1% on the invoice total in points. These points can be collected and used as a virtual currency to pay the next shopping.
  - 0.2% is used for marketing purposes and special promotions.
- Most of the shops have no BI tools in place, cannot afford, and host complex systems. Furthermore, there is a lack of IT knowledge and skill set.

The customer loyalty program itself is supported by the government in order to keep people shopping within the country.

4. Data analysis and expanded functionalities

Remark: only customers making use of the customer loyalty card are represented in the data, but there is certain proportionality to the population. Due to the signed non-disclosure agreement with the collaborating loyalty card provider, it is not allowed to show the real quantities. Therefore, the following visualizations are missing a y-axis. Nevertheless, trends and issues are clearly visible.

4.1. Data Analysis

Analyzing the existing data before the digital transformation revealed a negative trend in card usage and participating shops.

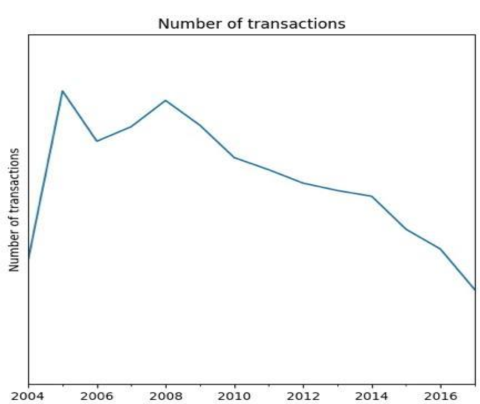

Figure 2: Number of customer transactions

The overall transactions booked with the loyalty card show a strong negative trend since 2008. The same trend can be observed with the participating shops. Both, Figure 2 and Figure 3, indicate that the loyalty card system became less attractive over the years.

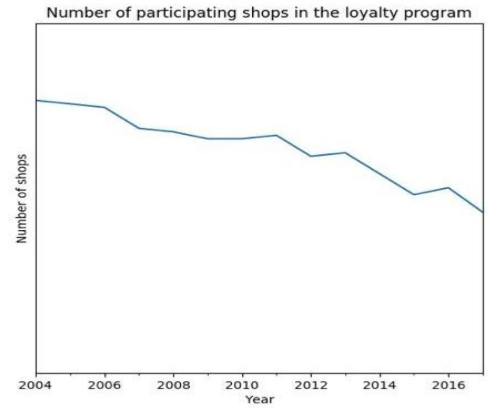

Figure 3: Number of participating shops in the loyalty program

Besides these negative trends, the analysis of how many customers regularly use the card shows more stability. Figure 4 shows that the customers using the card at least once per year is rather stable, since the introduction of the card in 2004. This indicates, that a certain customer group regularly uses the loyalty card. Furthermore, it shows that the card is not completely forgotten, unaccepted or unused.

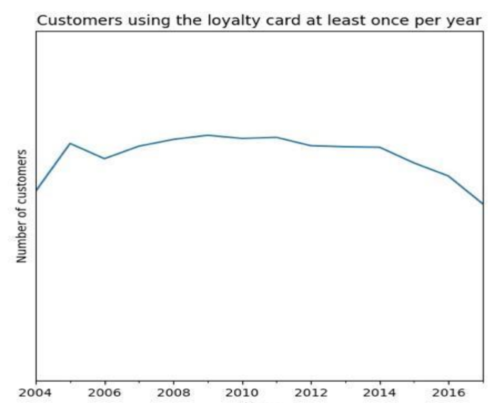

Figure 4: Usage of the loyalty card

Further analysis revealed that the main users are customers between 40 and 55 years old.

4.2. Expanded BI functionalities for stores

Graphical visualizations are one key aspect of BI solutions and are very useful for generating insights and for strategic decision-making [13, 15]. With the outdated card-based solution, shop owners had no possibility to analyze trends, as data was just stored but not used. Through the new implemented web application, shop owners have access to dashboards visualizing key performance indicators, such as trends, number of customers, number of transactions, turnover reactions, as well as visualizing seasonality effects. This creates a real value for small shops, since many of them rely only on experience and own calculations.

Therefore, the developed web application for shop owners provides a set of visual dashboard reports. In the following paragraphs, data from shop 25 were chosen for illustration purposes.

Figure 5: Number of transactions for shop 25

One of these visual dashboards in the web-application, represents the yearly, monthly and daily number of transactions (Figure 5 & Figure 6). Based on this information, shops can improve their workforce and capacity planning. Furthermore, seasonal trends can be visualized and addressed. For shop 25, in December a higher activity is observed, compared to the rest of the year. Following, some examples out of interviews, conducted with shop owners. One of the participating farmer stores has flexible opening hours and can benefit from additional information on seasonality and rush hours. Another shop owner owns several paper shops and needs information about the number of transactions (Figure 5) and sales data (Figure 7) to optimally plan and share workforce between the locations.

The next visualization illustrates the generated loyalty points by the customers of shop 25, indicating trends in sales in year 2016 (Figure 6).

Figure 6: Loyalty points generated by customers in shop 25

The loyalty points generated per weekday (Figure 7) reveals trends within the week and can be used in addition to Figure 5 to optimize workforce planning. Furthermore, insights in sales and turnover can be generated.

Figure 7: Loyalty points generated by customers in a week in shop 25

Both dashboards empower shops to obtain a better overview of their current business. Moreover, tailored advertising and marketing campaigns can be launched and their influence on the number of transactions, number of customers, and resulting sales can be studied.

For example, shop 34 spends money for advertisement on public transportation and newspapers. With the new visualization and reporting capability, shop 34 can study the effect of the marketing campaign on the number of customers and the sales in the following months.

4.3. Expanded BI functionalities for the government

The analysis level can be expanded to industry level, showing the loyalty through the number of customers for different industries over time. As an example, the number of customers in flower shops is visualized in Figure 8. The strong decline in the number of customers in the year 2008 was due to closedowns of several flower shops. The created BI tool includes dashboards on industry level that could be used by the local government as a tool to analyze the economic health of industry sectors, additionally to other tools. Consequently, economic help can be offered for industries being in a tight economic situation to maintain a sustainable and diverse economy with different industries. The major advantage is that data is accessible in real-time and minimal effort is needed to generate these additional dashboards.

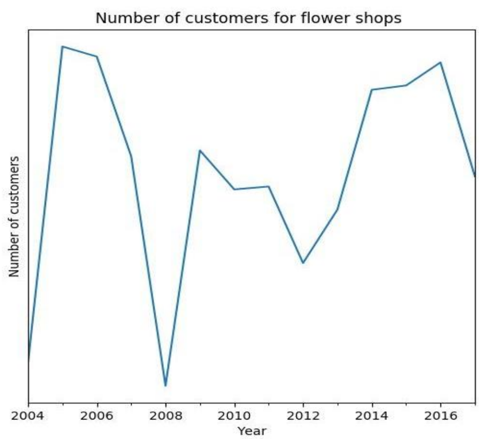

Figure 8: Analysis on industry level (example with all flower shops)

5. Strengthening collaboration between shops across various industries

5.1. Association Rule Mining

As discussed earlier, association rule mining can help to understand the shopping basket and can be used for up- or cross-selling products. In the existing case study, no such fine granular data existed. However, data on shop and industry level was collected and the association rule mining was applied to this data. Two example rules are stated in the table below. The first rule is mined on shop level. 7.1% of all customers bought products in shops 25, 98 and 128. When a customer has bought products in shop 25 and 98, there is a 73 % chance that a purchase in shop 128 will follow in the future (Table 1). The association rule mining can also be performed on industries as seen in the second rule. Customers' buying flowers in a flower shop buy with a high chance also print products in one of the paper shops (71%).

Table 1: Association Rule Mining

Antecedent	Consequence	Support	Confidence	Lift
25, 98	128	0.071	0.73	2.88
Flower	Print & Paper	0.157	0.71	1.34

For shops within the loyalty program new possibilities for cooperation arise. With the card-based system each shop offered the same rewards in form of loyalty points. With the new system new rewards can be developed for example in form of vouchers, to strengthen collaboration between shops across industries. For instance, customers making purchases in shops 25 and 98 get a tailored voucher with a discount on products offered by shop 128. Motivated from the literature [8, 19], the effectiveness of a loyalty program can be increased when the offered rewards match the customer needs. This result matches previous research of Capizzi & Ferguson [9], where cooperation in a loyalty program has been identified as one success driver.

5.2. Single Value Decomposition

When increased cooperation in a loyalty program is one success factor [9], deriving knowledge about existing and possible cooperation is fundamental. As the SVD is not only a dimensionality reduction technique but also mines latent concepts, it is suitable for deriving also latent shop clusters. The customer-shop matrix of the RFM with the standardized visits per shop is used as input data. Through the matrix decomposition, the "concept-to-shop" matrix V is derived. Through using a graph visualization tool, the top three connections of shops within each concept are visualized. The result is depicted in the following Figure 9. Each concept has its own edge color. For instance, one cluster of shops out of the analysis, that have something in common are shops 128, 97, 98. Conducting further research, we found out, that all these shops are located near the city center. Therefore, customers often visit all of these shops during their shopping day. As seen in Figure 9, all kind of clusters can be derived and further analyzed. As described in chapter 5.1, it can even be calculated, how high the probability is, that customers which were for example visiting shop 84 and shop 90 afterwards visit shop 129.

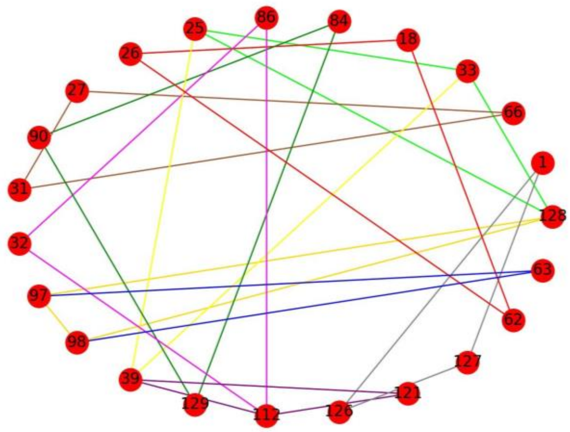

Figure 9: Derived shop clusters through SVD - Shops with similar characteristics

Shops within one cluster share similar characteristics e.g. frequency patterns. Often this information was not used in the past as it is latent. A strong similarity between shops in the latent cluster can be used for joined marketing campaigns, closer collaboration, special offers or customized rewards. In this way, shopping behavior and the shopping route of customers can be influenced.

On the one hand, this can increase the attractiveness of a loyalty program for shops to participate. On the other hand, customers benefit from special offers and rewards.

5.3. External factors

The loyalty program operates in a geographical area with multiple city-centers from different countries close to each other. Consequently, the different currencies from the countries seem to have a strong influence on the performance of the loyalty program and the shopping tourism. In Figure 10 and Figure 11 an overlap in the trend between the generated loyalty points and the currency exchange rate can be recognized. The financial crises in 2008 had not just a negative impact on the exchange rate (Figure 10), but also on the shopping behavior and the loyalty program (Figure 11). In 2010 and 2011 the financial crisis impacted different European countries in their repayment of debts [11]. The difficult financial situation can also be seen in the trend of the loyalty point generated, leading to a significant downturn. In the year 2015, the fixed exchange rate between the Swiss Franc and Euro was cancelled [20].In consequence, the Swiss Franc increased its value against the Euro and the exchange rate decreased [20]. This decline is also clearly visible in the trend of the loyalty points leading to the second drastic downturn (Figure 11).

It can be concluded that the economic situation impacts the business situation of small brick-and-mortar stores significantly. Furthermore, the hypothesis can be stated that there is a trend of shopping tourism as the price level and the exchange rate make shopping in the foreign currency economically more attractive.

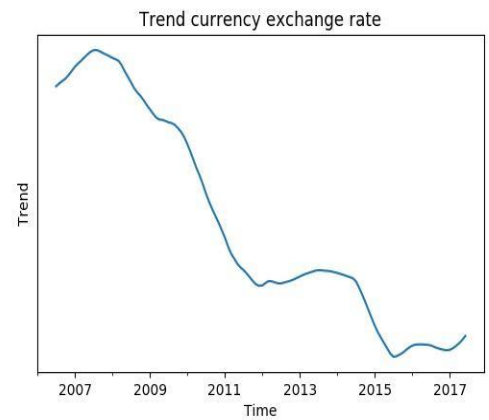

Figure 10: Currency exchange rate of Euro in Swiss Francs

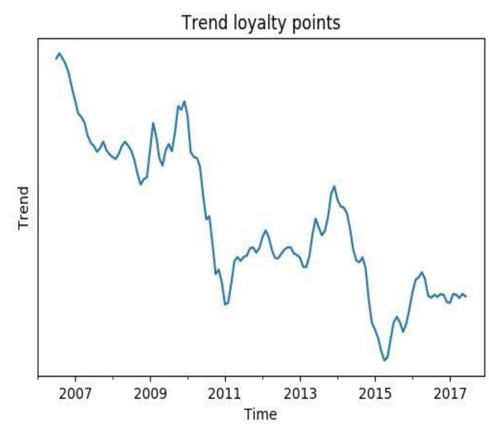

Figure 11: Total generated loyalty points

6. Main Findings

During the project work, development, analysis and implementation phases of the new loyalty program with extended BI functionalities, the following key findings were derived:

1) Deriving knowledge about company performance is essential in order to adapt to

external factors and changes. Therefore, a BI system for small shops becomes important. A loyalty program could offer additional services to analyze and strengthen the position of small brick-and-mortar stores.

2) Association rule mining can be applied on different granularity levels. With mining knowledge about associated shops, new reward types can emerge from the cooperation between shops across different industries. This can increase the value of the loyalty program.

3) SVD generates additional insights into the latent connection of shops. Therefore, very valuable and senseful collaboration possibilities can be derived. Based on this, joint marketing and promotions across various collaborating shops can be established.

4) External factors have a vigorous influence on the performance of the loyalty program. Exchange rate and foreign politics seem to influence the customers' shopping behavior and need to be considered in all actions from the loyalty program and its shop partners.

The data analysis revealed, that extended data analytics techniques can be integrated into loyalty programs. Such advanced loyalty programs provide many benefits for small brick-and-mortar stores, which cannot afford own complex BI systems. BI functionalities such as visualization of trends allow shop owners to gain additional insights and offer the possibility to make enhanced strategic decisions.

Cooperation between shops across industries can be used to strengthen the economic power of a region [9]. Additionally, this cooperation can facilitate the resistance to external challenges, such as currency exchange rates and price index fluctuations. However, loyalty programs need to expand their services.

As the loyalty program is the connection between the shops, industry and local government it is a powerful foundation for developing a strong and stable economic region. Transforming the core business model of a loyalty program from card-based system to a multi-service and platform provider is necessary to reach that goal. Moreover, the loyalty program can improve its attractiveness and creates revenue from selling these services to members in the loyalty program.

7. Implications

In the case study, it is shown that small enterprises can generate valuable business insights from data collected by a loyalty program. Due to the data structure in this case study, simple analysis methods like exploratory data analysis, association rules for shopping basket analysis and SVD for deriving latent shop clusters are applied. As most of the small enterprises participating in the loyalty program have no BI system in usage, information about current trends in customer shopping behavior is considered being very useful for strategic decision-making. Developing an analytics platform for the shops and transforming the loyalty program from a card-based system to a digitalized service, offering analytics and using cross industry data, can set the foundation for innovative loyalty program structures.

Moreover, it is necessary that brick-and-mortar shops, being part of a common ecosystem, need to cooperate in the future more closely to develop customized and attractive rewards for different customer types. Observing and measuring the impact of exchange rates on the customers' shopping behavior, might be also of interest for local governments to establish and maintain a sustainable economy through financial and economic politics.

8. Limitation and future work

The study is limited to a single case which has been studied intensively over two years. The limitations of this study are therefore related to the specific case settings described in chapter 3. Furthermore, the available features and variables of the data limits the development of further BI services.

The target of the new system is to increase the number of participating shops, as well as to increase the goods turnover and value creation in the country.

Therefore, future work includes the continues improvement of the BI services and web application design. In addition, the value of the new solution needs to be quantified in terms of increased customer loyalty and business improvements. Another interesting aspect is the acceptance rate of customers using the mobile solution compared to the old card-based system.

9. Conclusion

Operating own BI and analytics solutions for individual small brick-and-mortar shop are not possible due to costs and maintenance constraints. Scaling these solutions for multiple shops via a common loyalty program makes the analytical service attractive and affordable. A loyalty program with extended BI tools and capabilities can support small brick-and-mortar shops in gaining insights in recent developments, planning workforce, identifying trends and seasonal effects.

Through the transformed loyalty program, shop owners benefit from data analysis and dashboards, they did not have before. Furthermore, such an overarching system can be used to enhance the collaboration between shops across industries, offering joint promotions and discounts.

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