IoT Data Analytics in Retail: Framework and Implementation

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Abstract: IoT data analytics has many potential applications in the retail industry. However, relations among ambient conditions at stores as measured by IoT devices and sales performance are not well understood. This paper explores sensory and sales data provided by a large retail chain to quantify the impact of air quality, temperature, humidity and lighting on customer behaviour. It has been determined that the air quality and humidity have a significant impact and temperature appears to have a non-linear effect on customer behaviour. The data analysis findings are used to configure an IoT data analytics platform. The platform is used to monitor the ambient conditions in retail stores, to evaluate a need for improving the conditions as well as to enact improvement by passing them over to a building management system.

1 INTRODUCTION

Customer experience is a paramount to the retail industry. It has many dimensions such as sensorial, affective, physical, social and cognitive (Lemon and Verhoef 2016). In the case of brick and mortar retailing, vendors have to make any effort to retain customers and to compete with on-line shopping (Misra et al. 2017). The customers should be offered a comfortable and enjoyable environment. Modern computing and data processing capabilities provide opportunities for measuring and improving customer experience. Internet of Things (IoT) is one the technologies allowing to measure conditions at retailing facilities and data analytics processes these measurements to elaborate solutions for improving the customer experience. IoT helps businesses to harness and process data to improve operations and increase customer satisfaction (Shrikanth 2016). Automation opportunities of IoT help service industry in reducing costs and improving customer service. IoT enables the concept of constant connectivity to provide complete picture of on-going retailing processes (Berthiaume (2019).

However, the current trends indicate that the retail industry lags other industries in usage of the IoT technologies (Shanhong 2018) what could be caused by lack of understanding of relations between customer experience and environmental conditions as measured using IoT devices. That requires empirical investigations analysing sensory information in relation to sales data and customer behaviour (Ben-Daya 2019). Additionally, deployment of IoT devices and supporting data analytical solutions is a complex endeavorment and requires sophisticated technological platforms (Weyrich and Ebert 2016). The solution should be setup-up according to the results of data analysis and continuously operated to monitor conditions at retailing facilities and to enact improvements.

The objective of this paper is to empirically test relations between environmental conditions in a retail store and customer behaviour as well as to outline a technological solution for deploying IoT data analytics. The paper considers data analysis case study using data provided by a large retailing company. The data set and problem description are made available by the European Data Incubator program. Statistical data analysis is performed what yields rules for setting up a system used to control the environmental conditions. An IoT data analytical platform is proposed for hosting these rules as well as for monitoring the current environmental conditions. The contributions of the paper are practical quantification of relations among the environmental conditions and customer behaviour and sales performance as well as a proposal for implementing the results of data analysis.

The rest of the paper is organized as follows. Section 2 discussed applications of IoT in retail and customer experience dimensions. Empirical data analysis is reported in Section 3. Section 4 outlines a solution for implementing the results of IoT data analytics. Section 5 concludes.

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2 FRAMEWORK

To better understand value of using IoT analytics in retail, customer experience dimensions are analysed. A brief literature review is conducted on IoT applications in retail.

2.1 Dimensions

The customer experience and behaviour are influenced by many factors. The theoretical analysis of existing research is conducted to identify these factors with focus on suitability of IoT technologies for addressing these factors. The customer experience dimensions are summarized in Table 1. They concern various aspect of customer journey and some of them are within retailer's control (e.g., service interface, retail atmosphere, assortment, price) whole others are outside of the retailer's control (e.g., influence of others, purpose of shopping) (Verhoef et al. 2009). The identified dimensions are categorized 10 groups (Figure 1 shows the number of research works considering the dimensions belonging to a category).

Table 1: Dimensions of customer experience.

Author	Dimensions
Parasuraman (1988)	Reliability, Responsiveness, Assurance, Empathy, Tangibility
Schmitt (1999)	Sensory (sense), Affective (feel), Cognitive (think), Physical (act), Social-identity (relate) experiences
Wolfinbarger (2003)	Website design, Fulfilment/Reliability, Security/ Privacy, Customer service
Parasuraman et al. (2005)	Efficiency, Fulfilment, System availability, Privacy
Fornerino (2008)	Sensorial, Affective, Physical/ Behavioral, Social, Cognitive
Gentile et al. (2007)	Sensorial component, Emotional component, Cognitive component, Pragmatic component, Lifestyle component, Relational component.
Verhoef et al. (2009)	Social environment, Service interface, (Retail) Store atmosphere, Assortment, Price and promotions (including loyalty programs), CEs in an alternative channel, Retail brand, Past customer experience.
Lemke et al. (2011)	Communication encounter, Service encounter, Usage encounter
Klaus & Maklan (2013	Product experience, Outcome focus, Moments of truth, Peace of mind
Kim and Choi 2013	Service outcome quality, Interaction quality, Peer-to-peer quality
Handayani 2019	Accessibility, Competence, Customer recognition, Willingness to help, Personal treatment, Problem solving, Fulfilment of promises, Value for time

The most frequently considered dimensions are in affective, sensory, customer service and fulfilment/reliability. Some of these elements can be controlled by retailers. Traditional product presentation now has less impact than sensations as what customers see, feel, hear and touch (Arineli and Quintella 2015). Bagdare (2015) observes that customers' mood and behaviour depend on many elements like - music, lights, colours, displays, fragrances, soft and cozy ambience. Thus, the dimensions "affective", and "sensory" are more important in customer experience analysis. Consumers perceive shopping as a mode of relaxation, free-time activity or a habit. New expectations and needs have been created from changes in people's lifestyle and increased comfort Sathish and Venkatesakumar (2011). These observations confirm that ambient or environmental conditions are very significant aspects of the affective and sensory dimensions of customer experience. IoT analytics is well suited to measure and interpret of these conditions.

2.2 IoT in Retailing

IoT technologies have found many applications in retailing. The industry survey shows that 37% of food and grocery companies already experiment with IoT technology or have successfully initiated IoT services or products and further 58% are planning to expand their utilization of the technology (Irish 2017). IoT helps to improve both internal operations and customer facing processes. Patil (2017) identifies a number of operational benefits including personalization, dynamic pricing, inventory tracking and monitoring, and recommendations. Energy efficient smart thermostats and lighting are also mentioned. Sensors provide real-time stock information what is used to improve demand forecasts and optimize inventories (Kolassa 2019). IoT improves monitoring and control by coding and tracking objects (Madakam et al. 2015). That allows companies to become more efficient, accelerate processes, decrease errors and avoid theft (Gaur et al. 2017). The real-time data provided by sensors allows stakeholders to make better operational decisions (Balaji and Roy 2017).

IoT-connected smart labels provide means for identification of products as well as for providing additionally information (Fernandez-Carames and Fraga-Lamas 2018a). This information can be combined with personalization and recommendation services to enrich shopping experience with pervasive displays and smart things (Longo 2013). IoT provides means to engage customer throughout the product life-cycle (Fernandez-Carames and Fraga-Lamas 2018b). For example, smart textiles can communicate with smartphones to process biometric information. The life-cycle support requires an adequate IoT architecture ensuring efficient and secure data processing.

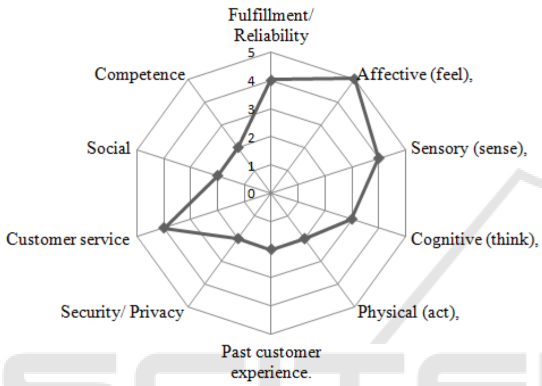

Figure 1: Categorization of customer experience dimensions and their frequency of mentioning in research works.

To summarize, retailers use IoT for inventory management, product tracking, equipment control and customer engagement. From the customer perspective, the existing research focuses on customer service, customer experience and fulfilment dimensions. However, there is little work on using IoT in relation to the impact of ambient or environmental conditions on customer behaviour in retailing. Therefore, this paper focuses on the sensory dimension and the impact of environmental conditions on the customer behaviour. That is conceptually represented as an IDEF0 activity in Figure 2. An IoT platform is used to harness sensory measurements of the environmental conditions. These are used by a Building Management Systems (BMS) to alter environmental controls and to improve the environmental conditions at a retail store. That should result in improved sales performance. In order to achieve that, relations among the sales performance and the sensor measurements should be understood to properly configure BMS.

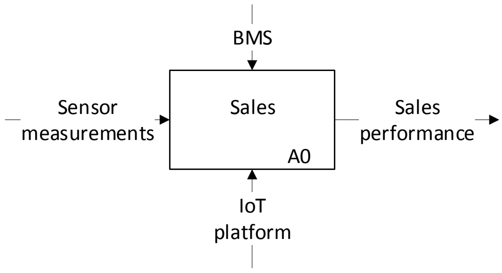

Figure 2: The IDEF0 model of the sales activity.

3 DATA ANALYSIS

Empirical data are used to investigate relationships among the environmental conditions, customer behaviour and sales performance. The data are provided by a large retail chain (more than 2000 stores and 30.000 employees), which have accumulated sensor measurements in their stores are well as sales data (EDI 2019). The data are gathered over the period from February 25th, 2019 till March 3rd, 2019 with store's operating hours 8:00 am to 10:00 pm. The data come from a single store and contain more than 60 000 purchase lines or registered transactions. The purchase lines belong to more than 7000 purchase orders. Over 150 000 sensor measurements are available for each sensor. The sensor data are not recorded strictly at the specific time intervals and there are missing data.

The company aims to interpret the effect of the ambient conditions of the stores in customer behaviour (EDI 2019). The main question for the analysis is about the effect of lighting conditions, temperature and humidity on the customer basket size. That involves determining thresholds for unfavourable ambient conditions. The company also expects to have a technological solution in the form of a decision support system that can analyse the IoT data along with the transactions in the store. The sensor data provided include measurements of air quality (higher values correspond to worse air quality), humidity, lighting and temperature. These can be used to control the affective and sensory aspects of customer experience. All customer transactions are recorded and the following sales performance measurements are considered in this investigation:

- Number of items (N)– number of different products purchased by a customer in one store visit (i.e., number of items in shopping basket);
- Weight of purchases (W) – weight of all products purchased by a customer in one store visit;

- Quantity of items (Q) – quantity of items of all products (summed across all types of products) purchased by a customer in one store visit.

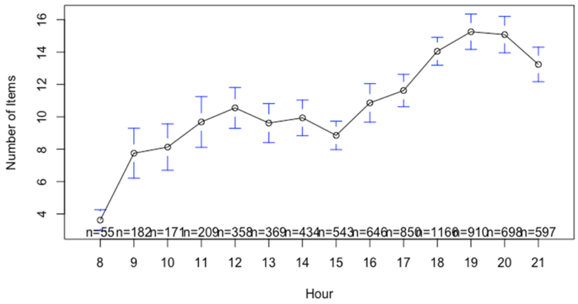

Figure 3: The average number of items N in the shopping basket by hour.

The value of transactions is not a part of the data set and names of products are not known. It is assumed that the measures indirectly characterize sales performance (i.e., a large number of items implies better sales performance) and customer behaviour (e.g., their willingness to pick-up more items and carry more weight).

After data pre-processing (e.g., standardizing data recording frequency for the sensors and treatment of missing data), the statistical analysis is carried out to identify relationships among the environmental conditions as measured by the sensors and sales performance and customer behaviour. It is identified that the shopping behaviour depends on the hour of the day (Figure 3). It can be observed that the purchases are relatively stable from 9:00 to 16:00 and they increase significantly from 17:00 to 22:00. The number of transactions increases gradually throughout the day till 18:00 and then gradually decreases. The environmental conditions also vary significantly depending on the hour. However, every environmental indicator has a different pattern. The air quality is the best around the noon and deteriorates in the afternoon as the busiest shopping hours approach (Figure 4). The pattern suggests that the air quality controls are only partially aligned with the customer behaviour. The lighting measurements have very distinctive spike at 13:00 and have significantly lower value from 16:00 and on.

In order to analyse relationships among the customer behaviour and the environmental conditions, the ANOVA analysis is conducted. The linear model is considered is:

$$N^*_{sj} = \mu + air + light + hummidity + temp + \varepsilon_{sj},$$

where s refers to the sensor group, j refers to the individual measurement, $N^*_{sj} = \ln(N_{sj})$ logarithmic transformation of N to reduce data skewness, ε_{sj} is the random noise. *air, light, humidity* and *temp* refer to air quality, lighting, humidity and temperature sensor measurements, respectively. The results (Table 2) confirm that the hour of the day significantly affects the customer behaviour. The air quality and humidity are the most significant factors of the sensory factors. The lighting is a statistically significant impact at the 5% significance level. The temperature appears not to have a significant impact on the customer behaviour. Similar results were also obtained for the weight of purchases and quantity of items.

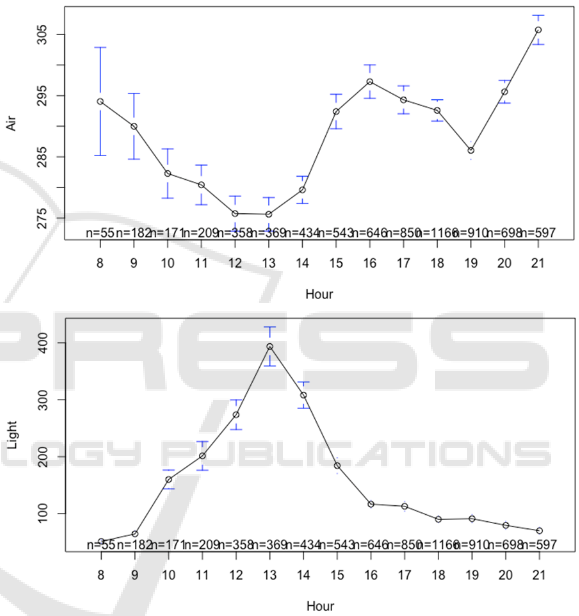

Figure 4: The impact of time on environmental conditions: the average air quality by hour (upper pane) and the average lighting by hour (lower pane).

To reduce noisiness and to improve interpretability of the relations, the sensor measurements are factorized in quintiles of equal number of observations. The number of items depending on the category of sensor measurements is reported in Figure 5. The figure suggests that the number of items purchased decreases if the air quality is low. The number items purchased is by approximately 50% smaller in the 5th quintile than in the 2nd quintile. The relative decline of the number of items purchased in the 1st quintile (the best air quality) can be explained by interactions between the air quality and hour of the day factors. The number of items purchased is relatively stable according to the

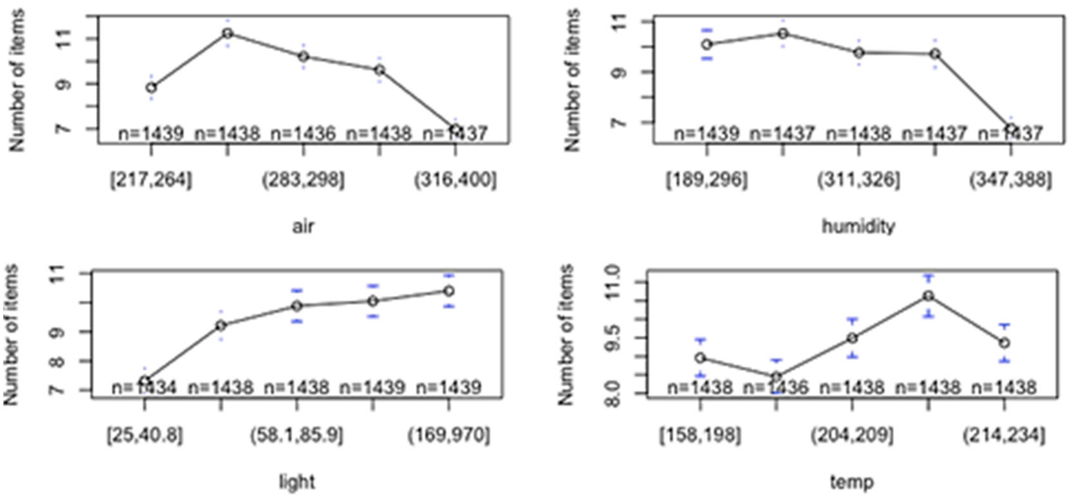

Figure 5: The average number of items *N* according to the quintile of sensory measurements.

humidity factor in all quintiles but the fifth. Improved lighting gradually increases the number of items purchased. The ANOVA analysis showed that the temperature is not a significant factor although Figure 4 suggests that there are non-linear relation customers not liking either too cold or hot conditions. The number of items purchased is the largest if temperature is in the fourth quintile. These observations are useful to formulate rules for managing environmental conditions to be used in the IoT platform. Figure 6 illustrates dependence of weight *W* of purchases on the environmental conditions. It confirms that the performance measures *N, W* and *Q* used to represent the customer behaviour follow the similar pattern.

Table 2: The ANOVA analysis of N^* according to hour and sensory measurements.

Sensor	DF	Sum Sq	Mean Sq	F value	P
Air	1	60	60.1	59.13	0.000
Light	1	4	4.2	4.138	0.042
Humidity	1	85	84.8	83.41	0.000
Temp	1	0	0.3	0.301	0.583
Hour	1	435	434.9	427.9	0.000
Residuals	7182	7299	1	1	

4 IMPLEMENTATION

A suitable technological solution is used to implement the findings about the relations between customer behaviour and the environmental conditions. The solution is a platform integrating data from IoT devices and other data sources, evaluating a need to improve the environmental conditions and invoking a building management system to enact the improvements. It is adopted from previous studies on context aware and adaptive systems (Kampars and Grabis 2018).

Component of the IoT data analytics platform is shown in Figure 7. Stream processing units K_m are responsible for receiving raw data from data providers (1) and handling internal data streams. The archiving jobs store the data in persistence storage and evaluation jobs use the raw data to evaluate the environmental conditions and the evaluation results are sent to internal stream processing (4), where they are forwarded for evaluation by triggering jobs used to invoke improvement actions (6). If triggering conditions are met (7), an improvement action is generated and posted to BMS (8,9). All potentially computationally intensive tasks are executed in dedicated containers in a cluster to ensure high performance. SP is implemented using Apache Kafka streaming platform. Evaluation jobs are built using Apache Spark big data analytics engine and the adaption engine is based on Docker containers. The infrastructure is provided using CloudStack cloud infrastructure tools.

In the case study considered, IoT data analysis yielded that if the air quality deteriorates beyond the lower boundary of the air quality 5th quintile, it should be improved (i.e., by powering AC) to avoid decreasing sales. This results in implemented in the IoT data analytics platform. The air sensor is one of the IoT devices providing data.

The platform continuously measures environmental conditions and compares them with the threshold. Figure 8 shows the air quality and sales

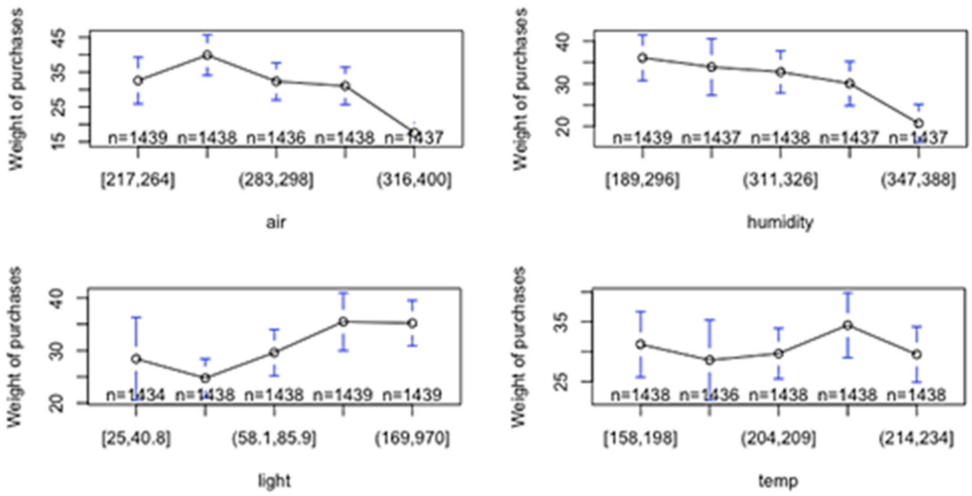

Figure 6: The average weight of purchases *W* according to the quintile of sensory measurements.

data according to time. It can be observed that occasionally the air quality exceeds the acceptable level, which is specified as a lower boundary of the fifth quintile of the air quality. The analytical suggests that this deterioration of the air quality leads to decreased sales. Upon these circumstances, the IoT data analytics platform should trigger an action to improve the air quality by BMS. In this case, the improvement logics is relatively simple while the platform allows implementation of logics of arbitrary complexity.

The platform continuously measures environmental conditions and compares them with the threshold. Figure 8 shows the air quality and sales data according to time. It can be observed that occasionally the air quality exceeds the acceptable level, which is specified as a lower boundary of the fifth quintile of the air quality. The analytical suggests that this deterioration of the air quality leads to decreased sales. Upon these circumstances, the IoT data analytics platform should trigger an action to improve the air quality by BMS. In this case, the improvement logics is relatively simple while the platform allows implementation of logics of arbitrary complexity.

There are various alternatives to the proposed platform and comprehensive comparison is beyond the scope of this paper. The main advantages of the platform are the use of open technologies, ability to integrate various data providers, decoupling of information requirements from data supply and separation of IoT analytics from the core BMS system. The decoupling allows to setup the system in various stores in a large chain, where different types of sensors might be used. The separation allows delegation of computationally intensive tasks to the platform without overloading BMS and using the IoT analytics with various types of BMS as well as other systems used in customer relationships management. The platform is horizontally scalable for application in large retail chains and can benefit from data exchange among the stores.

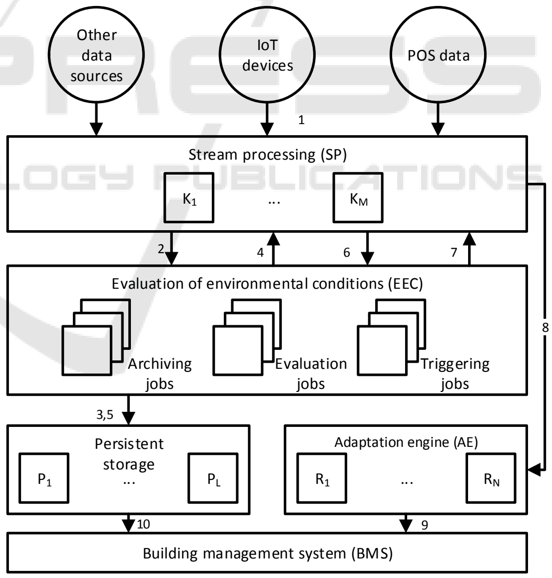

Figure 7: Components of IoT data analytics platform.

5 CONCLUSION

The empirical data analysis of relation among the environmental conditions and customer behaviour as well as sales performance has been conducted. It has been shown that the results of the analysis could be

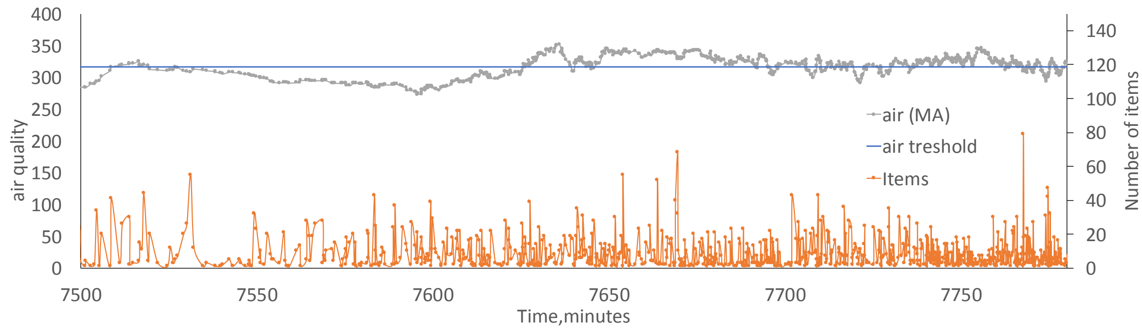

Figure 8: The air quality changes and the number of items (N) according to time.

used to configure the IoT data analysis platform for enactment of improvements of the environmental conditions. The statistical analysis shows that the sales performance is significantly affected by the air quality and humidity. The temperature appears to have a non-linear impact on the customer behaviour. The static analysis of historically accumulated data is performed in the paper. Dynamic adjustment of the data analytical models is possible as well as integration of real-time point-of-sales data for dynamic pricing and personalized recommendations.

The current study uses only already observed data and does not consider what kind controls have been applied to alter the environmental conditions and implementation of the proposed controls is necessary to check actual impact on customer behaviour and sales performance.

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