OPTIMISATION OF THE ASSORTMENT THROUGH E-COMMERCE CHANNELS FOR AN FMCG RETAIL COMPANY USING DATA ANALYTICS TECHNIQUES ON BIG DATASETS

Zhantileu Segizbayev, B.Sc. Mechanical Engineering
Saida Zhunussova B.Sc. Chemistry
Madina Baizhanova B.Sc. Radioengineering and Telecommunications

Submitted in partial fulfilment of the requirements for the degree of
Master of Engineering Management

NAZARBAYEV UNIVERSITY

School of Engineering and Digital Sciences
Department of Civil & Environmental Engineering

In partnership with the
Graduate School of Business

53 Kabanbay Batyr Avenue,
Astana, Kazakhstan, 010000

Supervisors: Prof. Dimitrios Emiris
Prof. Maria Tsakalerou

2021

Declaration

We hereby declare that this report entitled “Optimization of the assortment through e-commerce channels for an FMCG retail company using data analytics techniques on big datasets” is the result of our own project work except for quotations and citations which have been duly acknowledged. We also declare that it has not been previously or concurrently submitted for any other degree at Nazarbayev University.

Zhantileu Segizbayev

Saida Zhunussova

Madina Baizhanova

Abstract

The e-commerce market has been increasingly growing worldwide within the last years. With the spread of the COVID-19 pandemic and the strict lockdown conditions, many businesses, including retail firms, started moving to the online format. In Kazakhstan, the companies that are willing to gain a competitive advantage also adopted selling through online channels. The largest fast-moving consumer goods (FMCG) retailer in Kazakhstan, Magnum Cash&Carry, decided to enter the e-commerce market during the pandemic by launching Magnum Go online shopping mobile app. Due to the limited time constraints, the company did not adopt its wide range of assortment to the preferences of online customers. Thus, the primary goal of this paper is to improve the product assortment of Magnum Go, considering the findings of the literature review, comparison of sales, competitor's analysis, and benchmarking. Moreover, the further objectives include developing new categorisation and listing algorithm and evaluation of Magnum Go mobile app ergonomics.

The methodology consisted of three main approaches: data collection and pre-processing, data analysis and inference, and data visualisation. Besides, this paper describes using practical data analytics tools such as Microsoft Excel and Tableau for data processing and representation. The literature review outlines the role of applying big data analytics in e-commerce, the importance of assortment management, categorisation and listing strategies, and web and mobile app ergonomics.

The research results include the following parts: analysis of Magnum's offline and online sales, competitors' analysis, new categorisation and listing, mobile app ergonomics assessment, and interactive dashboard. The sales analysis of two different channels revealed the variation in customers preferences. The product assortment in offline and online stores, therefore, should also differ. Competitor analysis allowed comparing the company's assortment size with leading Russian FMCG retailers. The results showed that Magnum offers a considerably higher number of non-food products. Besides, this paper proposed implementing new categorisation and listing based on the extensive sales and competitors' analysis. Finally, the assessment of mobile apps indicated some areas for improvement in the functionality and interface of Magnum Go.

Acknowledgements

We would like to express our deep and sincere gratitude to our capstone supervisors Dr. Dimitrios Emiris and Dr. Maria Tsakalerou for their invaluable guidance throughout this research project. This study could not be completed without their patience, motivation, and immense knowledge. We would also like to extend our gratitude to representatives of the Magnum company, Mr. Andrey Lebedev and Ms. Olga Novitskya, for giving us a great opportunity to do research and to gain practical skills. Finally, we would like to express our sincere appreciation for our families and friends for their tremendous support.

Table of Contents

List of Figures

List of Tables

1. Introduction

1.1. Background information

In the 1990s, the wide adoption of the internet brought a broad range of possibilities, including a new promising communication channel. Many commercial businesses saw it as an opportunity to interact with potential customers that could reduce operating costs. Benefits such as displaying products on digital shelves, replacing cashiers with online payment systems, and reducing the supply chain complexity were quite tempting. It also transformed a shopping experience for consumers allowing them to purchase products at any place and time while expecting delivery to the front door. Therefore, numerous companies adopted the distribution of goods and services via online platforms, which marked the beginning of e-commerce (Dos Santos et al., 2017; Oláh et al., 2019). As many digital marketplaces emerged and e-commerce proved to be an efficient platform for selling goods, different business sectors joined this venture, including a fast-moving consumer goods (FMCG) retail industry. Studies predict that the online FMCG market will be one of the largest e-commerce sectors with an annual spent of $100US billion by 2022 (Dillahunt et al., 2019). It might come true due to the recent global pandemic of Covid-19 coronavirus, which accelerated the penetration of e-commerce (Bhatti et al., 2020). Many countries have introduced restrictive measures to curb the spread of coronavirus, including national lockdowns. During such periods, people were obliged to stay at home according to quarantine measures and were allowed to leave if strictly necessary. As a result, the pandemic triggered a change in consumer behaviour, and many people started to adopt online shopping. A study conducted by Kim (2020) shows a rapid increase in the number of online shoppers; among 2200 surveyed US citizens, 66% of young people (18-24), 68% of middle-aged people (25-40), 73% of older people (41-60), and 68% of retired people (60+) started to shop grocery online more regularly because of the pandemic. According to the author, although many people were purchasing consumer goods online long before the coronavirus outbreak, it accelerated the structural change in buying behaviour, making e-commerce the primary shopping method. The global trend has not spared Kazakhstan. During the pandemic, e-commerce market performance improved, with revenues constituting 0.5% of Kazakhstan's GDP (Alfonso et al., 2021). The reason behind such market growth might be the growing number of companies adopting an online shopping business model during the national lockdown.

1.2. Company information

Magnum Cash&Carry - the largest retail chain in Kazakhstan can be an example of e-commerce development catalysts in the country. Its history started in 2007 with a small store located in one of the residential areas of Almaty. Since then, the company has undergone a marvellous transformation from a simple grocery store to a leading firm in the Kazakhstani retail industry. Currently, the company operates 93 stores in 10 cities of the country, with more than 10 thousand employees. Magnum positions itself as an innovative company - always seeking ways to improve the customer experience while maintaining low prices for products. The company's mission statement is as follows: "We improve the quality of life while maintaining the family budget every day." This statement describes the primary competitive advantage of the company – cost leadership. According to the company's statements, the prices for Magnum products are 5-7% lower than average prices on the market. Despite being a cost leader, the Magnum is improving customer experience in various ways. For example, at the beginning of last year, the company released their loyalty card program, called "Magnum Club", for better understanding and analysing customer behaviour. With transaction data obtained from this program, Magnum adjusted its assortment strategy based on customer preferences, increased the efficacy of sales promotion using personalised offers, and decreased the average time customer spend in a line by introducing self-checkout stations. Overall, Magnum is shaping the whole retail industry of Kazakhstan. Their innovations are setting trends in the FCMG sector and increasing the quality standards for competitors.

1.3. Problem statement and motivation

Like many other retailers, Magnum experienced demanding challenges in the face of the ongoing pandemic. As a national lockdown was prolonged several times at the beginning of 2020, the declining number of in-store customer visits became a threatening problem that was difficult to assuage. Therefore, Magnum decided to implement an audacious strategic move and resolve the difficulty in a sedulous manner. The company entered the e-commerce market by launching a mobile application for online grocery shopping - Magnum Go. Due to financial losses caused by quarantine measures, they had to develop this grocery delivery service in a tight schedule, which resulted in several flaws. One of which is an assortment of products presented in Magnum Go that is not optimal for the digital market. An abundance of products on Magnum Go that is not suitable for e-commerce makes navigation for online buyers challenging, which, in turn, alienates potential customers from using a new service. Hence, the primary challenge that the company is currently facing is to recognize and understand the needs of consumers who shop online and offline in its stores. It has become apparent that the assortment may not be entirely suitable for the e-commerce context and runs the risk of suboptimal satisfaction of the customer demands.

1.4. Project scope and aims

The objective of the present research, therefore, is an enhancement of assortment for online customer needs. Thus, the study focuses on conducting four primary analysis: comparison of the offline and online channels, comprehensive competitor analysis and benchmarking, analysis of categorisation and listing principles for e-commerce, and analysis of web ergonomics of the Magnum Go app. Firstly, the research aims to conduct a statistical analysis of sales history from offline and online platforms and compare them. The scope of this analysis includes an overview of product class and group sales, analysis of sales by time and location parameters, identification of average basket composition, and estimation of various statistical characteristics of the data. It helps in differentiating customer needs of people who shop online and customers who prefer visiting stores. Secondly, this study aims to perform a detailed analysis of competitors' assortment. It includes analysing competitors' categorisation on different levels, product width and depth in assortment strategy, product listing and arrangement algorithms, category naming and listing methods. Thirdly, the present work focuses on analysing categorisation and listing techniques to build a new assortment that is suitable for the e-commerce platform. The scope of this part covers creating a new categorisation, improving a list of stock-keeping units (SKU) for optimal satisfaction of customer needs, and building improved listing algorithms. Finally, the research team concentrates on performing a web ergonomics analysis, which assesses the Magnum Go app and competitors' apps for user interface and experience (UI and UX). This analysis includes gathering customer feedback on current UI and UX, testing apps according to different key performing indicators (KPI), and performing statistical analysis of apps' UI and UX efficiency.

1.5. Expected outcomes

The expected outcomes of the present research, therefore, are the following:

i. comprehensive competitor analysis and benchmarking for identifying best practices;
ii. a new categorisation improvement for e-commerce customer needs;
iii. a product listing algorithm optimised for increasing the company's profit and satisfying customer needs;
iv. an in-depth examination of Magnum Go's and competitors' web ergonomics;
v. an interactive dashboard for conducting real-time analysis and forming performance reports.

1.6. Structure of the thesis

The present thesis consists of four primary parts: literature review, description of conducted research, results and discussion, and recommendations with concluding notes. The literature review provides a comprehensive scientific basis for the research completed in the paper. The description of conducted research part includes a detailed depiction of the data collection and pre-processing procedures. In addition, this part explains data analysis procedures and data analytics tools used in the process. Finally, this part describes data visualisation methods and interactive dashboard tool. The research results include comparative analysis of Magnum offline and online sales, competitor analysis and benchmarking, the new categorisation of assortment for e-commerce, new listing algorithms, web ergonomics analysis of Magnum Go application and competitors' platforms, and presentation of the interactive dashboard. Eventually, the present paper will conclude the research outcomes by providing recommendations for the future development of the e-commerce platform.

1.7. How research is related to the program

The current project primarily focuses on data analytics. However, it also touches on different fields of engineering management and business. For example, it covers several parts of the Master of Engineering Management (MEM) program curriculum, such as statistics, engineering economy, business strategy, finance, accounting, marketing, understanding consumer behaviour, big data management, and service operation management. In the first part of the study, while analysing offline and online sales of

Magnum company, the knowledge and skills learnt in courses such as Advanced Probability and Statistics, Finance, and Big Data and Information Management were used in conducting the analysis. Additionally, the theory learnt in the Understanding and Predicting Consumer Behaviour was also helpful in identifying differences in online and offline consumer behaviour. Secondly, during competitor analysis, knowledge gained in Marketing, Accounting, and Production and Service Operation Management was essential to conduct in-depth research of competitors' business. Overall, this project provided an excellent opportunity to gain hands-on experience of being a manager and solving real-life business challenge faced by a large company. It was practical in obtaining empirical knowledge by applying the theory learnt during the MEM program.

2. Literature Review

The literature review mainly consists of four dimensions: the application of big data analytics (BDA) in the e-commerce sector, assortment strategy, categorisation and listing strategies for e-commerce, and the importance of web and mobile app ergonomics for online retailers. The section about data analytics in e-commerce outlines the main effects, benefits, concerns, and tools. In the next part of the literature review, the impact of assortment strategy on companies' performance and customer satisfaction are analysed. Besides, it describes the assortment development and improvement methods. Furthermore, we reviewed categorisation and listing strategies for online businesses, including the role of category management. The last section is about web and mobile applications ergonomics, including features, usability studies, and the sophisticated design of e-commerce platforms on sales and customer experience.

2.1. Data analytics in e-commerce retail

Within the last years, BDA has attracted considerable attention from both research academia and the e-commerce industry. According to Akter and Wamba (2016), this phenomenon occurred since the implementation of BDA allows e-commerce companies to be at least 5-6% more productive than their competitors that do not apply BDA. However, the concept of BDA remains under-explored, which presents an impediment for its further development. By conducting the systematic literature review, authors revealed that the implementation of BDA might create the following business values: needs identification, market segmentation, decision making, and improvement of company's performance, new product/market/business model innovations, and creating infrastructure and transparency (Akter and Wamba, 2016). On the other hand, this paper does not provide information on the recent trends of BDA in e-commerce, considering the ever-changing e-commerce environment and technological advancements that happened over the past several years.

Today stores offer thousands of SKUs for their customer by generating a large number of transactions. Managers can use this volume of data for effective data-driven transformations and modifications in a company. Le and Liaw (2017) state that nowadays, due to the complex and highly competitive nature of the business world, companies should base their decisions on all available data types. The data can have structured, semi-structured, or unstructured forms. The application of BDA can bring a variety of benefits to companies, specifically within e-commerce channels. It can help online retailers ascertain how to increase the retention rate of their consumers in the most effective manner.

In the past few years, the application of BDA in retail e-commerce has had an increasing trend. However, in 2020 COVID-19 pandemic caused a tremendous boost in technological progress and a dramatic increase in customer demand; these, in turn, have led to e-commerce growth (Arora et al., 2020). The authors also revealed the three critical elements for a successful response to this growth: building, testing, and learning culture in a company, operations that would support rapid reactions to new customer demand, and centricity on customers. The last two elements highly depend on collecting and analysing customer data. Nearly half of the best-performing businesses apply BDA weekly or even more frequently to reveal new ways of meeting ever-changing customer demand (Arora et al., 2020).

Despite the benefits of the application of BDA in retail e-commerce mentioned above, there are some concerns regarding data accuracy and data security (O'Raghallaigh, 2015). However, these issues are often raised when data is collected from customer surveys in experimental settings and the data relevance criteria are not clearly defined to make the information unbiased. Moreover, BDA challenges associated with the balance between technical complexity and managerial implication (Ansari and Li, 2018). As in the case with the benefits, challenges of BDA offer a variety of opportunities for the firms to gain competitive advantage and improve the value proposition.

Big data analytics is a field that continuously develops and progresses, requiring new skills and capabilities. They are some relevant procedures described in the literature that can be used as a guide to big data processing and analysis. Gandomi and Haider (2015) identify two main BDA processes. The first is data management, and it includes five stages: acquisition and recording; extraction, cleaning, and annotation; integration, aggregation, and representation. The second process type is analytics which consists of two different stages: modelling and analytics; interpretation. The two stages of analytics processes are mostly related to value creation and improving customer experience. To make data-driven decisions, companies have been implementing a variety of tools with different features and benefits. According to the 2021 Gartner Magic Quadrant for Analytics and Business Intelligence Platforms, Microsoft Power BI and Tableau were positioned to be the market leaders (Richrdson et al., 2021). These tools are not only helpful in terms of big data processing but also enable effective data visualisation and representation. Overall, there are many retail e-commerce fields that can benefit from the application of BDA, one example of which is assortment strategy.

2.2.Assortment for e-commerce platforms

The product assortment plays one of the most crucial roles in retailing strategy. There are diverse definitions of assortment strategy among retail and marketing research papers. One of the most common definitions used is that the assortment is the variety of products offered for consumers (Broniarczyk and Hoyer, 2006). The two main attributes of the product assortment are the width and depth of the offered products. Assortment width refers to the total number of product categories (departments), while depth is the number of SKUs or product variations in each product category (Hart and Rafiq, 2006). In the book by Sysoeva and Buzukova (2019), an effective assortment should be optimal and comprehensive, efficiently utilize company resources, and achieve planned targets for turnover and profit.

At the end of the previous century, retailers mostly expected that a more extensive assortment gives the opportunities of targeting more customers. Retailers have been, therefore, adding new products to their product assortment very rapidly. According to Kök et al. (2015), from 1985 to 1992, the number of products on the retail market annually raised by 16%, whereas shelf space increased only by 1.6% per year. Nowadays, retail firms increase the assortment size rationally because statistics show that they can waste 46% of products per year due to stock-outs, end-of-life, or discontinuation of a relationship with a supplier (Morton, 2017). Also, with the more significant number of SKUs, the inventory management and supply costs raise. Recent studies suggest that assortment size optimization can improve the performance of the company. For example, the paper by He, Guo, and Chen (2019) revealed that both too narrow and too broad assortment size could lead to low performance in sales. It also aimed to disprove the common belief that the greater the assortment size, the more it gives a competitive advantage to the firm. Heese and Martínez-de-Albéniz (2018), in their studies about the effect of assortment size on market competition, emphasize that optimizing the assortment can bring the following benefits: improve operational efficiency, fit supply with demand, and finally, offering a smaller number of products simplifies the choice, making buying process for customers less cumbrous.

The assortment strategy could also depend on the type of store. Offline and online stores could have different constraints and various strategic objectives. For example, physical stores have shelf space constraints, while e-commerce platforms have online disutility costs. In a mixed type of store, some companies would prefer to use different pricing strategies and offer products of varying quality levels in brick-and-mortar stores and e-commerce platforms to maximize the expected profit (Shao, 2020). To determine the appropriate and effective assortment strategy for companies, the researchers suggest constructing an optimization model and develop an efficient algorithm. To maximize the assortment planning, Flamand et al. (2018) designed a mixed-integer programming model considering store-wide shelf space constraint, the profitability of product categories, expected demand, and their purchase potential.

Most traditional retailers are effectively applying assortment strategy; however, e-commerce business owners sometimes disregard this important aspect of revenue management. Online stores do not have shelf space allocation constraints; therefore, there is a higher probability of over-assortment than in brick-and-mortar stores. Similarly, as with offline stores, sophisticated assortment strategy in e-commerce channels can bring valuable benefits in inventory management and marketing strategies (Colla and Lapoule, 2012). Increasing the number of SKUs in the same product category produces additional costs and the complexity of choice. More importantly, if the product has a lower margin, its sales add less value than products with a higher margin (He, Guo, and Chen, 2019). In other words, companies may lose sales by selling less profitable products. It does not mean that e-commerce retailers can only offer a few products with high margins; they need to provide a diverse assortment to satisfy the target market and allow consumers to determine the features of products they need (Boysen et al., 2019).

Making assortment more efficient can include the following methods: evaluation of the product assortment of competitors and analysis of historical data (Besbes and Sauré, 2016; Petrova, 2019). The competitors' research and benchmarking can help to provide a bigger picture, determine similarities and trends in the assortment. At the same time, historical sales data allows assessing products purchase history and customers purchasing power. Also, McKinsey proposes to apply several KPIs for evaluating different products. The performance dimensions can include:

- Financial factors
- The uniqueness of the product

- End-to-end costs
- The role in the strategic objectives.

In the described pilot project, the reduction in the number of SKUs is projected to result in 1-2% growth in both sales and gross margins (McKinsey, 2019). Therefore, assortment decisions should not only be based on financial indicators but should include comprehensive analysis.

2.3. Categorisation and listing strategies for e-commerce

Once the store's assortment is established, the subsequent steps are to categorise the products and list them on the e-commerce platform. Product categorisation is helpful in many perspectives and can be applied in the following ways: new product development, product promotion, cannibalisation analysis between new and existing units, and general investigation of product dependencies within the same or different categories (Holý, Sokol, and Černý, 2017). Products are usually classified based on their usage, features, price level, brand, etc. Some studies describe the hierarchical approach, while others suggest alternative fuzzy clustering and possibilistic methods of clustering (Zhang et al., 2007; Ammar et al., 2016).

An adequately compiled product classifier is the resource that allows managers and suppliers to analyse the assortment and make decisions on its renewal and rotation. Authors from Russia who have spent more than 15 years studying product assortment and category management in retail distinguish three main division levels of product classification (Sysoeva and Buzukova, 2019). The first and the highest level is the class of products, and the bigger the size of the store, the higher number of product classes it would have. The second is the product group, a collection of goods joined by some common characteristics such as type of product, method of production, etc. The lowest division in the classification is the category of the products. It represents the set of goods that are similar for usage. Companies with a large assortment can distinguish more detailed levels of product subgroups and subcategories.

Category management implementation has led to the significant shift in modern retail from brand management to the whole category management (Sharif, 2012). It allowed focusing more on customer satisfaction rather than on brand promotion which improved retailing efficiency and returns on investment. The manufacturers create the brands; however, the category usually already exists and appears to be the basis for brand development. Although the brands are important in product selection and promotion, the main criteria in categorisation are customer needs (Karampatsa, 2017).

Holý, Sokol, and Černý (2017), in their work, have introduced a method for product categorisation in retail based on the customers' shopping experience. By analysing basket composition data, they investigated product dependencies within the same category and used this data for product clustering. In general, it is essential to mention that the products need to be grouped not based on the company's internal classification by category managers but on how customers perceive and understand them. For example, if a customer wants to buy cheese, it can belong to the group of "Diary products" from the category manager's perspective. In contrast, in the customer's mind, the cheese is usually related to products for sandwiches. In this case, the customer will more probably associate cheese with sausages rather than milk (Sysoeva and Buzukova, 2019). Therefore, customers perspective plays a crucial role in product categorisation.

Since e-commerce stores have various assortments, they are currently implementing modern technologies for product categorisation and listing. Ristoski et al. (2018) described machine learning (ML) for product categorisation and matching. These methods text classification to clustering products based on their title and description. Besides, companies can apply intelligent algorithms for product titling in e-commerce websites or mobile apps. For example, de Souza et al. (2018) emphasised that for large companies with hundreds of thousands of SKUs is not feasible to create product titles manually and proposed to employ an algorithm for automatic titling.

Thus, organising products into effective categories, groups, and classes produces a sophisticated categorisation that can improve inventory management and assortment planning. After the categorisation of retail e-commerce business is completed, the categories of products need to be adequately listed on a platform. It is considered to be a part of mobile app and web ergonomics.

2.4. Web and mobile app ergonomics

The term ergonomics is defined to be the "science of work", and it is derived from the Greek words *ergon* (work) and *nomos* (laws) (Bridger, 2018). According to the paper published in the Journal of Applied Ergonomics, this study investigates the interactions between humans and other system elements. It applies methods and data to design a system as a combination of coupled activities or items (Wilson, 2017). Ergonomics can include three critical types of constraints: accessibility, usability, and contextual conditions (Shorrock and Williams, 2016). Researchers can use these constraints to assess the effectiveness of the ergonomics of the system.

Some companies prefer websites as a platform for e-commerce stores, others use mobile apps, and the third type sells products through both channels. The early literature about the listing and platform design in e-commerce is associated with websites simply because mobile commerce is an incomer of electronic commerce (Jahanshahi et al., 2011). Both mobile app and website channels offer a unique set of benefits and have their challenges. Some literature argues that the difference in user behaviour in browsing e-commerce mobile applications and websites is not very significant (Einav et al., 2014). However, according to the studies, customers sometimes find it problematic to perform transactions or other activities smoothly via mobile app due to limited memory capacity, the size of the screen, simplicity of user interface, and small input methods (Ahmad and Ibrahim, 2017).

Nevertheless, the spread of using mobile phones can be observed; therefore, e-commerce businesses' interest in investing in mobile app design is also increasing.

The sophisticated design, consistent listing of product groups, precise navigation, and user-friendliness are elements of a website or mobile app ergonomics. E-commerce platforms are the main channels of communication; therefore, they play a significant role in attracting and retaining customers. Studies have shown that 93 % of users recognise the visual appearance of an e-commerce platform as a critical purchase decision factor (Thomas, 2016). Each element of the website or mobile app can affect the customer experience on a platform. For example, the brightness and the shades of the colours of e-commerce websites can affect consumer mood, memorisation, and purchase intention (Pelet and Papadopoulou, 2012). The paper by Soyanov et al. (2015) assessed the mobile apps based on the following dimensions: engagement, functionality, aesthetics, information, and subjective quality. For each of the dimensions, the authors proposed several criteria, which in total became 23. Schmutz et al. (2010) investigated the effect of product listing representation on sales and customer decisions and cognitive load. The authors provided and tested two types of product presentations: matrix and listing. The results revealed that with list presentation, users experienced less cognitive load and selected less expensive products. It can be explained by the second experiment in which the eye-tracking testing was performed, and it showed that the list presentation triggers more comparison movement than matrix design. Another finding by Van Der Heide (2013) determined the effect of product photographs on consumer behaviour. According to the experiment, the products with more realistic photos resulted in higher sales. Thus, the website's visual appearance or mobile app, product listing presentations, and pictures can add value to customer satisfaction and increase sales.

The customer-centric approach has become increasingly common among businesses within the last years. Due to the highly competitive market, focusing on customers' demand is especially essential for retail e-commerce firms. To gain more market share and competitive advantage, companies developed customer-centricity even more and implemented personalised services. According to Colla and Lapoule (2012), a customised website option is one of the critical success factors of an e-commerce store. Website usability studies also suggest that cultural factors such as regional, linguistic, and country features can be used to design a more personalised user interface (Díaz, Rusu, and Collazos, 2017). Providing a set of recommendations based on customers' preferences is quite popular nowadays. Lin (2014) reports that both user and system recommendations can positively affect the company's sales performance. Thus, companies can gain substantial benefits by designing a personalised interface of mobile app or websites.

3. Description of Conducted Research

This part of the report describes the processes, methods, and tools used to collect, pre-process, analyse, and visualise data. The section is mainly divided into three subparts: data collection and pre-processing, data analysis and data analytics tools, and finally, data visualisation and building interactive dashboards.

3.1. Data collection and pre-processing

According to Uma and Hanumanthappa (2017), data collection and pre-processing procedures are considered the most critical stages for acquiring quality data that can be further used for data analysis. This part discusses the procedures of collecting various data and its pre-processing for further analysis. Apart from that, it describes the rationales for collecting the data.

3.1.1. Magnum offline versus magnum go sales analysis

As it was previously stated, one of the main aims of this project is to improve the current product assortment presented in the Magnum Go goods delivery service. As of now, the product assortments presented in Magnum's offline stores and the e-commerce channel are entirely identical. However, as it was mentioned in the literature review part, the customer experience, and hence, the preferences of offline and online clients are distinct. Therefore, the following hypothesis is proposed: the preferences of Magnum's offline and online users are different. In order to either accept or reject this hypothesis, Magnum's offline and online sales performances will be analysed and compared with each other.

For this purpose, a dataset containing the sales data of Magnum's offline stores was downloaded from the company's QlikView Business Intelligence platform. The data pre-processing was performed before the download in the platform's data transformation and data preparation engine. The dataset includes the offline sales data for four months from October 2020 to January 2021 and is stored in the Microsoft Excel worksheet .xlsx format. The dataset contains the following variables: Date, City Name, Product Group, Product Category, Product Subcategory, Product ID, Product Name, Brand Name, Brand Name, and Total Sales. The dataset contains nearly seven million rows and therefore was stored in eight different Microsoft Excel worksheets. All the worksheets were loaded into a data analytics tool and appended to form one dataset.

Further, the sales data of Magnum Go for the same period was received from the company's contact person. The data represented a Microsoft Excel Binary Worksheet document in .xlsb format. Since this document format is not supported by data analytics tools such as Tableau and Power BI, the dataset was converted into a convenient Microsoft Excel Worksheet .xlsx format. After the dataset had been loaded into the data analytics tool, it was determined that the file consisted of two Microsoft Excel sheets. The first sheet stored the sales data for months from October to December of 2020 and consisted of almost one million rows. The second sheet stored the sales data for January 2021 and consisted of nearly four hundred thousand rows. Both sheets were loaded into the Microsoft Excel data analytics tool's data transformation and data preparation engine. After analysing the metadata of the sheets and making sure that the variables in both sheets had absolutely the same names and types, they were appended into a new query consisting of approximately one million and four hundred thousand rows and 19 variables. The variables of the data set were: Order ID, Product ID, Product Name, SKU, Barcode, Quantity at the beginning, Quantity at the end, Measurement Unit (item or kilogram), Unit Price, Total Price, Status, Store Name, Product Item Replacement Sign, SKU Status, Delivery Date, Order Status, Week, Month, Day. However, the variables such as Barcode, Quantity at the beginning, Status, Product Item Replacement Sign, SKU Status, Week, Month, and Day were deleted from the query since they were unnecessary and would not contribute to the data analysis. Therefore, this step resulted in a data set consisting of eleven variables. The further step was to ensure that the variables had the appropriate data types, i.e., Whole Number, Decimal Number, Text, or Date. After performing several minor adjustments to the columns' names and data types, the next stage was to check the quality of the data, i.e., whether the columns stored any error or null values. It was determined that the data in all the columns were 100% valid. The next step was to check whether the data contained any outliers. For this purpose, the interquartile range rule was applied. After identifying all the outliers in the dataset, they were eliminated.

However, the Magnum Go sales data did not have any variables storing the specific information about products ordered, i.e., the names of product groups, categories, and subcategories. For this purpose, the corresponding classificatory dataset was downloaded from the company's Business Intelligence platform, QlikView. The classificatory dataset contains the information about the products and has the following four variables: Product Group, Product Category, Product Subcategory, Product Name.

This dataset will be needed to analyse the Magnum Go sales data from the perspectives of product groups, categories, and subcategories and, therefore, will be included in the data model. Besides, a dataset containing data about the brand of each SKU sold in the Magnum stores was also downloaded from the QlikView platform. This dataset will help in defining the top-selling brands in each product group, category, or subcategory. Finally, apart from the Magnum Go sales data, the company provided the dataset containing specific information about orders. This dataset contains the following variables: Order ID, Order Date, Delivery Date, Quantity of ordered items, Delivery Price, Total Price, Delivery Status, Products Assembler Name, Products Assembler IIN, Courier Name, Courier IIN, Client Name, Client Telephone Number, Recipient Name, Contact Telephone Number, Delivery Address, Delivery Time Slot, Delivery Rating, Comments, Receipt, Store Name, Month, Day, Week, iOS versus Android sign, Year. However, after eliminating the unnecessary columns, the resulting dataset contains the variables of an Order ID, Order Date and Time, Delivery Date, Quantity of ordered items, Total Price, Client Telephone Number, Delivery Time Slot, and Delivery Rating. This dataset will help determine the preferable order time, delivery time slots, average order, and delivery rating, and other insights.

All the datasets mentioned above were added to a data model so that the Magnum Go sales data was assigned the role of a fact table, implying that it stored the data that would be analysed and aggregated. Meanwhile, the other three tables were assigned the role of a dimension table, meaning that they will be used for slicing and dicing the data in the fact table. The connections between the fact table and the dimension tables were set to have the cardinality of Many-to-One, respectively. The sales data was connected to the brands and the classificatory datasets using the common Product Name column. In contrast, the connection between the fact table and the orders dataset was established using the common Order ID column. Therefore, the resulting data model will enable performing Magnum Go sales data analysis from different perspectives.

To conclude with this subpart, the collected and pre-processed datasets will help analyse and compare the preferences of Magnum's offline and online clients. The datasets will be used to identify any differences in these preferences and further refining the current product assortment presented in Magnum's e-commerce channel.

.

3.1.2. Competitor versus magnum go analysis

As it was previously stated, the main objective of the capstone project is to improve the current product assortment of the Magnum Go goods delivery service. For this purpose, the preferences of Magnum's offline and online customers will be analysed and compared to each other to reveal any differences in them. The next step is to conduct competitor analysis and benchmarking in order to compare Magnum Go's product assortment with that of other online retailers operating in Kazakhstan and benchmark companies. As regards the competitors, after a thorough investigation, a variety of Kazakhstani FMCG online retailers were identified. However, it was determined that the major direct competitor of Magnum Go was the Arbuz goods delivery service. To benchmark, three leading online retailers operating in Russian Federation were chosen. The benchmark companies are Lenta (Lenta website and Lentochka mobile application), Perekrestok, and Utkonos. In order to determine and further compare the product assortments, the companies' websites and mobile applications were accessed, and the information on the width and the length of each product group, category, and subcategory were meticulously recorded into a Microsoft Excel worksheet in the form of a hierarchy. The worksheet represents a dataset consisting of the following four variables: Product Group, Product Category, Product Subcategory, and the Number of unique SKUs presented in each product subcategory. This data collection process continued nearly two weeks ad resulted in a Microsoft Excel document depicting the product assortments of Kazakhstani online FMCG retailer Arbuz, Russian benchmark companies Lenta, Lentochka mobile application, Perekrestok, and Utkonos. These product assortments will be further analysed and compared to the merchandise mix presented in the Magnum Go e-commerce channel. Additionally, the collected dataset will be used to evaluate and compare the categorisation, listing, and naming of product groups, categories, and subcategories in websites and mobile applications of competitors and benchmark companies.

Moreover, to compare the product assortment of Magnum's e-commerce channel with that of the company's direct competitor and benchmark companies, the data about Magnum Go's merchandise mix was downloaded from the company's QlikView Business Intelligence platform. The dataset contained Product Group, Product Category, Product Subcategory, and Product Name variables and more than sixty thousand rows. The dataset was combined with the worksheet containing the information about product assortments of Magnum Go's competitor and benchmark companies for ease of analysis and comparison.

The collected datasets will help analyse and compare Magnum Go with the chosen online retailers in terms of product assortment and further refine it. After conducting the competitor analysis and benchmarking, the next step in improving Magnum Go's product assortment is to analyse how products are categorised, listed, and named in the product catalogues of the investigated online retailers.

3.1.3. Categorisation and listing analysis

For categorisation and listing analysis, the data about the product assortment represented specifically in Magnum Go's mobile application was manually collected. The data includes information about the names of product groups, categories, and subcategories, how the products are categorised, and finally, the order in which the product groups, categories, subcategories are listed in the product catalogue. The data collection was performed by accessing the mobile application of Magnum Go, manually writing out all the necessary data, and recording it in a Microsoft Excel worksheet in the form of a hierarchy. The resulting document represented a dataset with three variables: Product Group, Product Category, and Product Subcategory. This dataset was mainly collected to analyse how products were categorised, listed, and named in the mobile application and would be further used for creating a new improved products' categorisation.

Additionally, to create an intelligent listing of products in a mobile application that would improve Magnum's sales performance, the products with the highest margin should be identified. For this purpose, the dataset containing the sales data of each SKU presented in Magnum's stores was downloaded from the company's Business Intelligence platform, QlikView. After performing data pre-processing in the platform's data transformation and data preparation engine, the following variables were chosen for the download: Product Group, Product Category, Product Subcategory, Product ID, Product Name, Sales Volume at a promotional price, Total Sales Volume, Sum of Sales at a promotional price, Total Sum of Sales, Total Cost of Goods Sold. The data was downloaded in the Microsoft Excel worksheet format and contained more than fifty-five thousand rows. Therefore, the resulting dataset contains all the necessary variables and observations for more than fifty-five thousand unique SKUs, which will be used for calculating the profit margin for each product sold at Magnum.

3.1.4. Web ergonomics analysis

As previously mentioned in the literature review part of the report, the way the products are represented on the online retailer's website or mobile application plays an essential role in the user experience and hence, the company's sales performance. Ergonomic representation of products includes their easily understandable names, the way they are listed, the easiness of finding them, to name a few. For this purpose, a survey consisting of eleven questions was carried out. The prepared questionnaire mainly asked respondents to evaluate and rate the mobile applications of Magnum Go, Arbuz, Lentochka, and Utkonos in terms of their performance, easiness of navigation, gestural design, graphical representation of products, groups, categories and subcategories, their layout, visual appeal, and finally, information quality and quantity. The collected survey data will be analysed and interpreted, and further recommendations to Magnum Go will be given based on the analysis.

Finally, to evaluate the easiness of finding a product and making an online order on a website or a mobile application, several tests were carried out. The primary purpose of these tests was to count the number of steps and measure the time required to find a particular product in the catalogue and place it in the basket. Besides, the total time required to make a complete online order was determined. For performing these tests, twenty different products were randomly chosen. The collected data will be used for performing analysis of the web and mobile applications of Magnum Go, its competitors and benchmark companies, and further preparation of recommendations.

3.2. Data analysis and data analytics tools

This part of the report discusses the methods, procedures, and tools used to analyse the collected data. Specifically, it will describe the data analysis methods and tools applied to analyse and compare Magnum's offline and online sales. Additionally, the approaches used to analyse the product assortments of Magnum Go, its competitors, and benchmark companies will be discussed. Besides, the methods used to analyse the data about products categorisation, listings, naming, and representations will be depicted.

3.2.1. Magnum offline versus magnum go analysis

In this section of the report, the methods, procedures, and tools needed to analyse Magnum's offline and online sales will be described. The first stage in Magnum's offline and online sales analysis was to ascertain the proportion of Food, Non-Food, and In-house production products in the total offline and online sales. For this purpose, pivot tables containing the columns of Product Class, Total Sum of Sales (absolute value), and Total Sum of Sales (per cent of total) were created. The Total Sum of Sales values were sorted in descending order. The results reflected in the pivot tables will be further analysed and compared to each other.

Further, the analysis of offline and online sales with a breakdown into product groups was performed. In doing so, pivot tables with the following columns were created for each product class: Product Group, Sum of Total Sales (absolute value), Sum of Total Sales (per cent of grand total). The Sum of Total Sales value was sorted in descending order. These analytics will allow identifying the most selling product groups in each of the product classes (Food, Non-Food, In-house Production).

Next, the offline and online sales were analysed in the context of cities where Magnum operates. To this end, a pivot table with the columns of City Name and the Sum of Total Sales was created. The Sum of Total Sales was shown as the per cent of the total and sorted in descending order. The results presented in the pivot table will reveal the most prosperous cities in terms of sales volume and will be compared to each other.

The further analysis of the Magnum offline and Magnum Go's sales data was conducted with a breakdown into the days of the week. For example, the average weekly revenue by weekday was identified for all the cities in which Magnum Go operates.

Additionally, the composition of an average offline purchase and an online order by product groups was determined. For this purpose, pivot tables with the following rows and columns were created: Order IDs in the rows, Product Groups in the columns, and the Total Price in the values. The Total Price values were shown as the per cent of the row total. Then, the column mean was calculated to determine the share of each Product Group in average online order and an average offline purchase. After grouping the column means by product classes, the average distribution of Food, Non-Food, and In-house production products in an offline purchase and online order was determined. Additionally, the average distribution of products broken down by product groups in the Food, Non-Food, and In-house production product classes were identified. The analysis of an average basket composition will help in understanding which products people buy on average.

The conducted analysis and comparison of Magnum's offline and online sales will help identify any differences in the preferences of offline and online users and further refining Magnum Go's product assortment.

3.2.2. Competitor versus magnum go analysis

The next step was to analyse the product assortments of Magnum Go, its direct competitor, and benchmark companies. First, the proportions of Food and Non-Food products in the total product assortments were determined. For this purpose, first of all, another column indicating the class of products (Food, Non-Food) was added in the Microsoft Excel worksheet containing the data on companies' product assortments. The new product class column stores only two unique values: "Food" and "Non-Food." Then, a pivot table with the following two columns was inserted: Product Class and the Sum of SKUs. The Sum of SKUs value was shown as the per cent of Grand Total. Similar pivot tables with the same columns were created for Arbuz, Perekrestok, Utkonos, Lenta, and Lentochka. The created pivot tables will enable to analyse and compare product assortments of Magnum Go and other goods delivery services in terms of the product classes.

The further step in the analysis was to identify the width of each product group in the Food product class for all of the compared online retailers. In doing so, a pivot table with the two following columns was built for Magnum Go's product assortment: Product Group and Sum of SKUs. The Sum of SKUs value was shown as an absolute value, and the corresponding column was sorted in descending order. Similar pivot tables were created for Magnum Go's competitor and benchmark companies. With the use of the created pivot tables, the product assortments of Magnum Go, Arbuz, and other online retailers will be analysed and compared to each other in terms of the groups in the Food product class. The same procedure was performed for product groups in the Non-Food product class.

Further, an analysis of the distribution of SKUs by product category in each of the product groups was performed. In other words, the proportion of product categories in each product group was calculated. For example, the distributions of SKUs by product categories of "Canned vegetables," "Canned fruits and berries," "Canned fish and seafood," "Canned meat and poultry," and "Canned milk" in the Canned Food product group were analysed for Magnum Go, its competitors, and benchmark companies. For this purpose, a pivot table with two columns of Product Category and Sum of SKUs was created for the Canned Food product group. The Sum of SKUs value was shown as the per cent of the grand total in the product group. The same pivot tables were created for all the forty product groups for all the investigated companies. Therefore, the created pivot tables will help understand how the products are distributed by product categories in product groups and compare these distributions between Magnum Go and its competitors and benchmark companies.

To conclude with this part, the product assortments of Magnum Go, Arbuz, and other online retailers were analysed and compared to each other from perspectives of product classes, groups, and categories. This analysis will help in further refining the current product assortment of Magnum Go.

3.2.3. Categorisation and listing analysis

This part of the report describes the methods, procedures, and tools used to analyse the collected data about categorisation, listing, and naming of products in websites and mobile applications of Magnum Go, its competitors, and benchmark companies. Firstly, product categorisations of all the online retailers were analysed. In particular, an analysis of how products are categorised into product groups, categories, and subcategories was conducted.

Further, the most common names of product groups, categories, and subcategories in the mobile applications and websites of competitors and benchmark companies were identified. Besides, these names were analysed in terms of their ease of perception. Based on this analysis, some of the product groups, categories, and subcategories were renamed for the Magnum Go product catalogue.

In terms of product listing, it was determined and further analysed which product classes and groups were displayed first in the product catalogues. Then, the arrangement of product categories and subcategories within each product group was identified and analysed. As a result of this analysis, the product groups, categories, and subcategories were rearranged for the Magnum Go product listing. Additionally, information on the margin of each SKU was used for a more beneficial representation of products in each group. Therefore, the products with the highest margins were displayed first in the corresponding product groups, categories, and subcategories.

3.2.4. Web ergonomics analysis

As previously stated, for performing the mobile application design ergonomics analysis, a questionnaire consisting of eleven questions was developed. The questions basically ask the respondents to evaluate the mobile applications of Magnum Go and other retailers from user experience and user interface perspectives. The answers to the questionnaire will be further analysed and presented later in the report. Besides, the results of the user experience tests will also be analysed and discussed later in the report. Based on this analysis, the recommendations to the Magnum Go mobile application will be given.

3.3. Data visualization and interactive dashboards

After collecting, pre-processing, and analysing the data, the next logical step is to build supportive graphs and interactive business dashboards. In this part of the report, the methods, procedures, and tools used to visualise the results of the analysis will be discussed. Besides, the software and tools applied to create an interactive dashboard will be described.

3.3.1. Data visualization procedures and tools

The data visualisation was at most performed in Microsoft Excel and Think-Cell software. The main types of graphs used for visualisation were a pie chart, a bar chart, and a column chart. A pie chart is a circular statistical graph which is represented by slices of different arc length to depict the corresponding proportion. This type of chart was used to visualise the offline and online sales of Magnum by cities and depict the basket composition of an average offline and online purchases. A variation of a pie chart, a doughnut chart, was used for depicting the distribution of SKUs by product categories within each product group. A bar graph is a chart where categorical data is represented by rectangular bars with lengths equal to the values they represent. The bar chart was applied while visualising and comparing the product assortments of Magnum Go and other online retailers from different perspectives. Finally, a column chart is a type of bar chart where the rectangular bars are plotted vertically. The column chart was used for the visualisation of Magnum's offline and online sales by product groups in each of the classes.

3.3.2. Interactive dashboard tools and procedures

Building an interactive dashboard was performed in the Tableau Business Intelligence software, one of the most powerful and modern data analytics and visualisation tools. As the initial step, the following four datasets were uploaded into the data preparation engine of the analytics tool: Magnum Go sales dataset, Products Information dataset, Brands information dataset, and finally, Orders Information dataset. The Magnum Go sales dataset is represented by more than one million rows and eleven variables. Meanwhile, the Products Information dataset contains the information about products, i.e., product groups, product categories, and product subcategories. This dataset is represented by nearly sixty thousand rows and four variables. Next, the Brands Information dataset contains almost sixty thousand rows and two columns. Finally, the Orders Information dataset contains specific information about orders and is represented by more than sixty-five thousand rows. All the datasets mentioned above were added into the data model with the cardinality Many-to-One. After creating the data model, the following eight graphs were constructed: a map of Kazakhstan, Sales by Product Group, Sales by Product Category, Sales by Product Subcategory, Sales by Brand, Number of Orders by Day of Week, Sales by Day, Forecasting. The map of Kazakhstan represents the four cities of Almaty, Nur-Sultan, Shymkent, and Petropavlovsk, where Magnum Go operates. Next to the name of each city, there is an indication of the corresponding sum of sales. Besides, the marks such as colour and size were used for better visualisation of data. The Sales by Product Group, Sales by Product Category, Sales by Subcategory, and Sales by Brand graphs were constructed in the form of horizontal bar charts where each bar represents the corresponding proportion of total sales. The bars are shown in descending order to demonstrate the top-selling groups, categories, and subcategories easily. The colour and label marks were applied in these graphs as well. Next, the Number of Orders by Day of Week and Sales by Day graphs were visualised using line charts. The line charts also use the marks of colour and label for better representation of data. Finally, the Forecasting line chart shows the forecasted sales for the next four weeks. For forecasting, Tableau software uses the exponential smoothing method. The next step in creating the dashboard was to add the dashboard cards at the top of the canvas that would indicate the key performance indicators such as Total Revenue, Number of Orders, and the Average Order Rating. Further, the following filters were added to the dashboard for ease of filtering the data: Select Month and Select Product Class. Besides, the "Use as a filter" option was used for the first four graphs for a more detailed visualisation and filtering. In other words, this option enabled to represent the sales performance for a specific city, product group, product category, and subcategory. The filtering applies to all the existing graphs and cards. The final step included adding the name of the dashboard and the company's logo. Therefore, all these stages resulted in an interactive business dashboard that would allow the representation and filtering of the sales data from different perspectives.

4. Results and Discussion

4.1. Comparative analysis of Magnum Go and Magnum offline

This part of the report demonstrates the results of the analysis and the comparison of Magnum's offline and online sales. As previously stated, the major purpose of this analysis was to understand how the consumer behaviour of Magnum's offline customers differed from that of online users. Based on this understanding, the product assortment presented in Magnum's e-commerce channel will be refined and improved. As it was mentioned earlier in the description of the conducted research, at the beginning of the project, the following hypothesis was proposed: the customer preferences of Magnum's offline and online clients are different. The following parts of the report will help to either accept or reject this hypothesis. The results of the hypothesis testing will contribute to the refinement and improvement of Magnum Go's product assortment strategy.

4.1.1. Sales analysis and comparison in terms of product classes

The first step in understanding the difference between the needs of offline and online users was to analyse and compare the sales of Magnum offline stores and Magnum Go with a breakdown into product classes. Figures 4.1.1. and 4.1.2. represent the shares of Food, Non-Food, and In-house Production product classes in the total Magnum Go and Magnum offline sales. First, what can be easily noticed from the presented figures is that the most preferred products for both offline and online clients are Food products. The share of the Food product class in the total Magnum's offline sales accounts for 86%. Meanwhile, for the Magnum Go sales, this share is even higher and amounts to 94%. Regarding the Non-Food products, their share in the total volume of offline sales amounted to only 5%, while for the online sales, this proportion was even less and accounted for 2%. Finally, the per cent of products produced in-house in the total volume of Magnum offline sales was 9%. As for the online sales, the share of the In-house production class was even lower and accounted for 4%. It can be concluded from the presented charts that although there is a strong preference for Food class products over other classes among both offline and online customers, this preference is even higher for online clients. Therefore, despite some existing similarities, the consumer behaviour of Magnum's offline and online customers from the perspective of product classes differs. The obtained insight will help improve the product assortment of Magnum Go and customise it to the needs of online users.

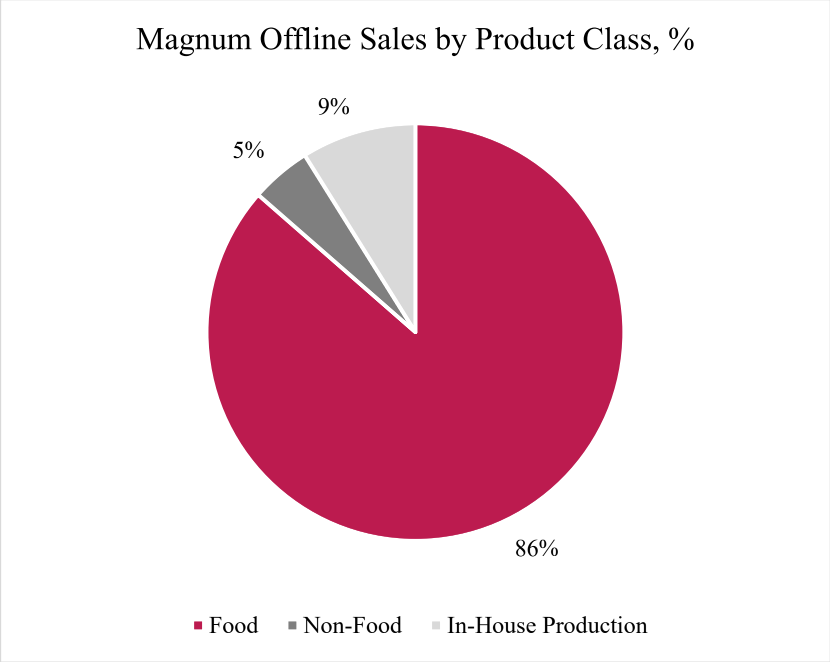


Figure 4.1.1. Magnum offline sales by Product Class

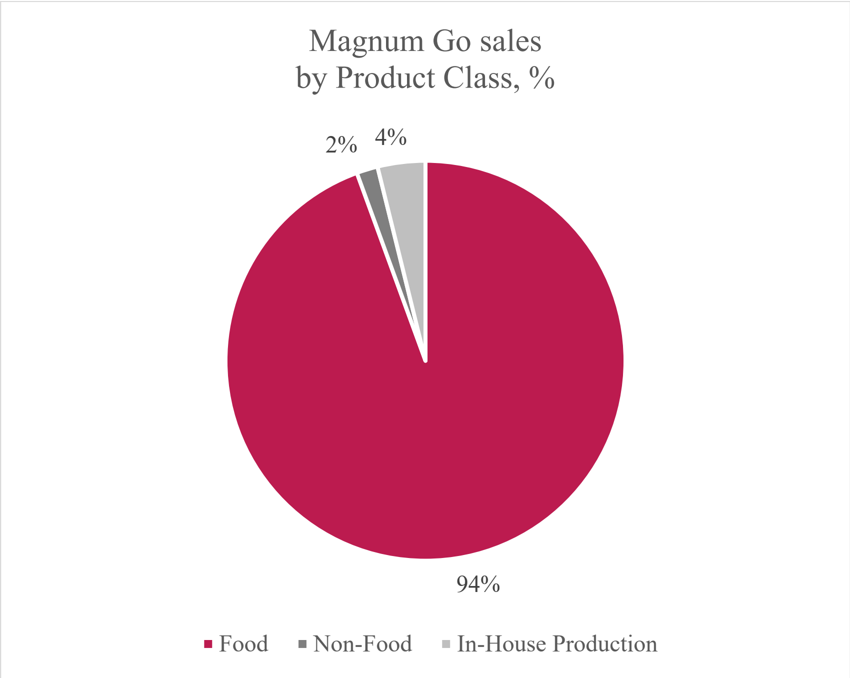


Figure 4.1.2. Magnum Go Sales by Product Class

4.1.2. Sales analysis and comparison in terms of product groups

The further step in identifying the differences in the online and offline customers' preferences was to analyse and compare the Magnum offline and online sales from the perspective of product groups. Figures 4.1.3. and 4.1.4. represent the sales distribution in the Food product class by product group in Magnum's offline stores and e-commerce channels. First of all, it can be easily observed from both charts that the top-seven product groups form almost 70% of the Food products sales. According to Figure 4.1.3., the top-seven Food product groups are Pastry and candy, Dairy Products, Pantry staples, Group of eggs, cheese, and sausages, Group of vegetables, fruits, berries, and mushrooms, Hygiene products, and Soft drinks. Meanwhile, suppose online sales are taken into consideration. In that case, the list of the seven most prevalent Food product groups starts with Dairy products followed by Pantry Staples, Group of Vegetables, fruits, berries, and mushrooms, Group of Eggs, cheese and sausages, Hygiene products, Household chemicals, and finally, Pastry and candy group. Although some of the product groups such as Dairy Products or Pantry Staples appear in the top-seven list for both offline and online sales, it can be clearly seen that their proportions in the total offline and online sales volumes are different. For example, the top-selling group for offline users is Pastry and Candy. However, for online users, the same group is in seventh place. This may be attributed to the spontaneous nature of offline shopping. Moreover, some groups do not appear in both top-seven group lists. These are Soft drinks and Household chemicals.

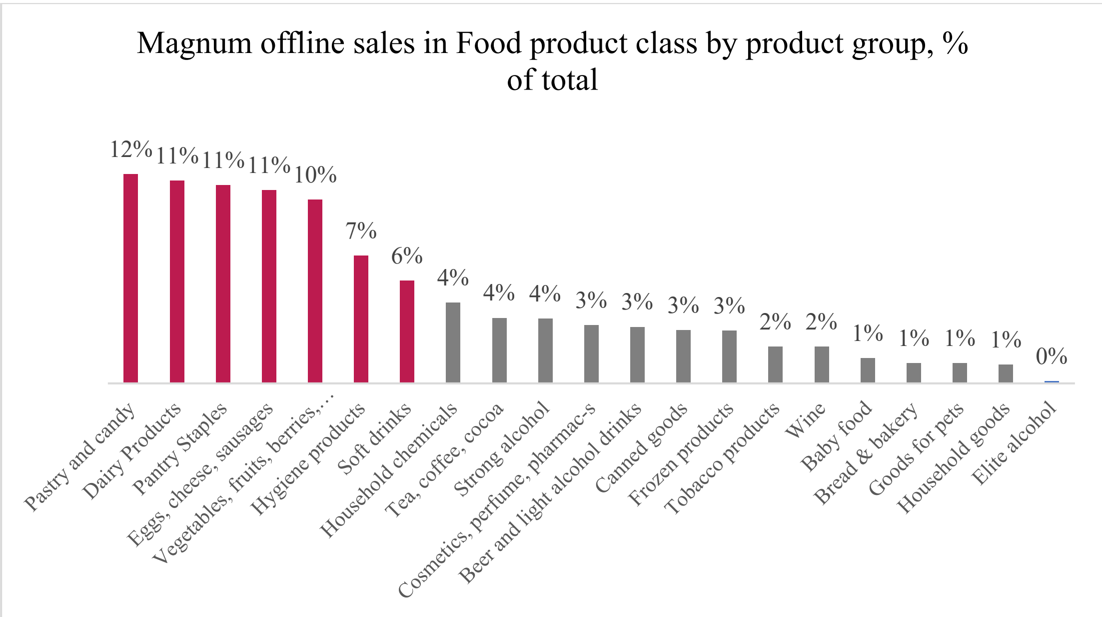


Figure 4.1.3. Magnum offline sales in the Food product class by product group

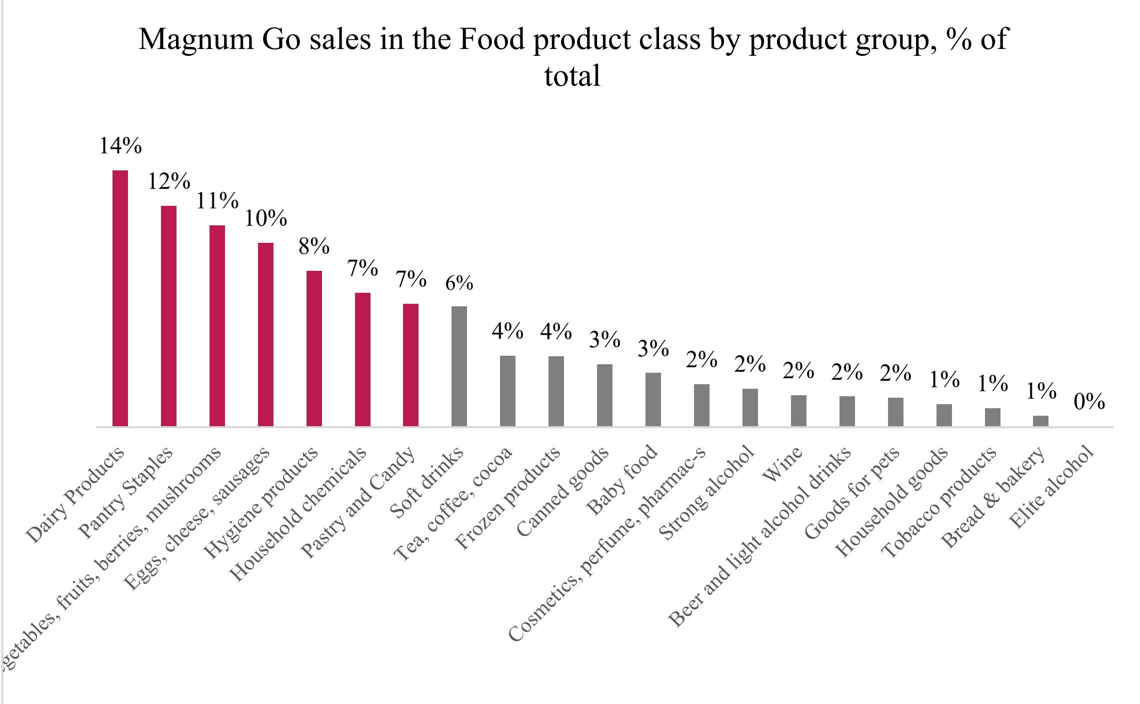


Figure 4.1.4. Magnum Go sales in the Food product class by product group

The offline and online sales by product group in the Non-Food product class are represented in Figures 4.1.5 and 4.1.6. In this case, 70% of the Non-Food product sales are represented by the first six product groups. It can be easily observed from both charts that the most selling Non-Food product group is the Household chemicals (26% for offline sales, 34% for online sales). Besides, several product groups such as Goods for kids, Electronics, and Home Textile appear in the top-six list for both offline and online sales. However, some differences can be observed here as well. For example, the product groups such as Party supplies & crafts and Hosiery & tights are listed in the top-six product groups for offline sales, but they are not included in the same list for online sales. Inversely, the top-six product group list for online sales contains Stationery products and Automotive goods groups that do not appear in the same list for offline sales. Therefore, it can be concluded that despite some similarities, the customer preferences of offline and online users for the Non-Food products have differences as well.

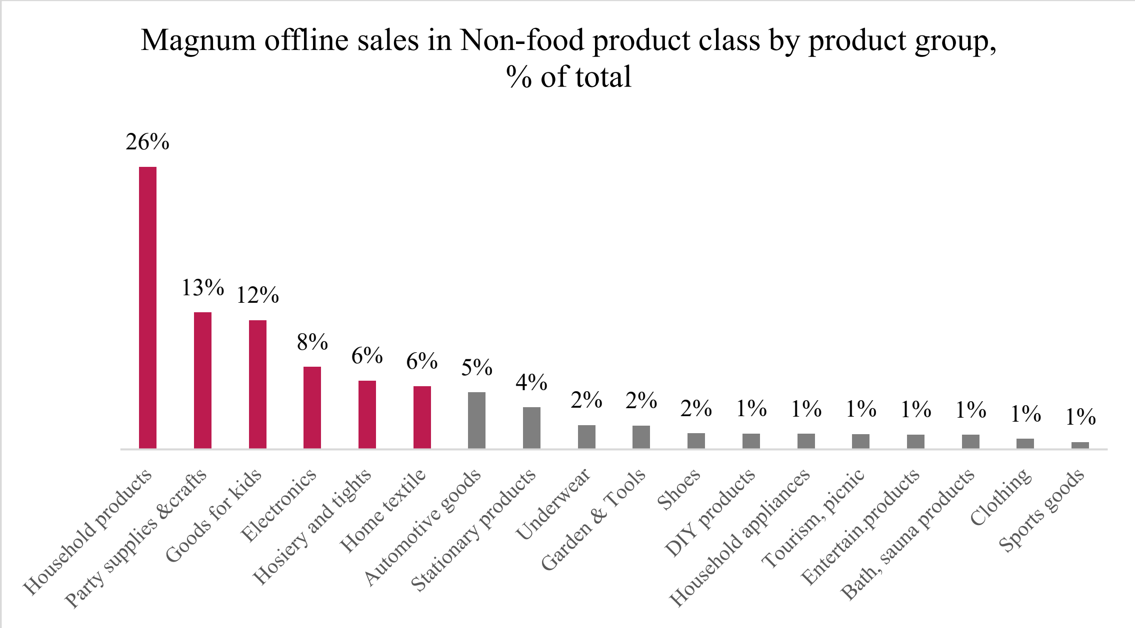


Figure 4.1.5. Magnum offline sales in the Non-Food product class by product group

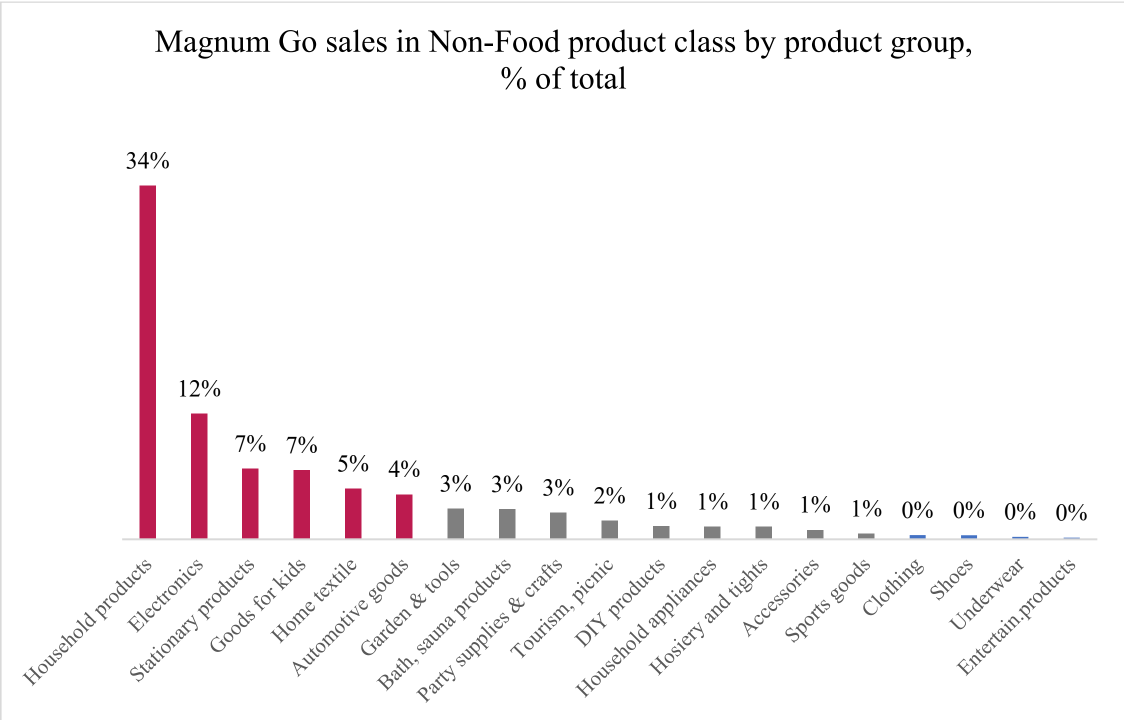


Figure 4.1.6. Magnum Go sales in the Non-Food product class by product group

Finally, the preferences of offline and online customers from the perspective of product groups in the In-house production class were analysed. From Figures 4.1.7. and 4.1.8. it can be clearly observed that the top-five product groups are identical for both offline and online sales, with the Meat products group being the most prevalent. However, the distribution of sales among these top-five groups is different.

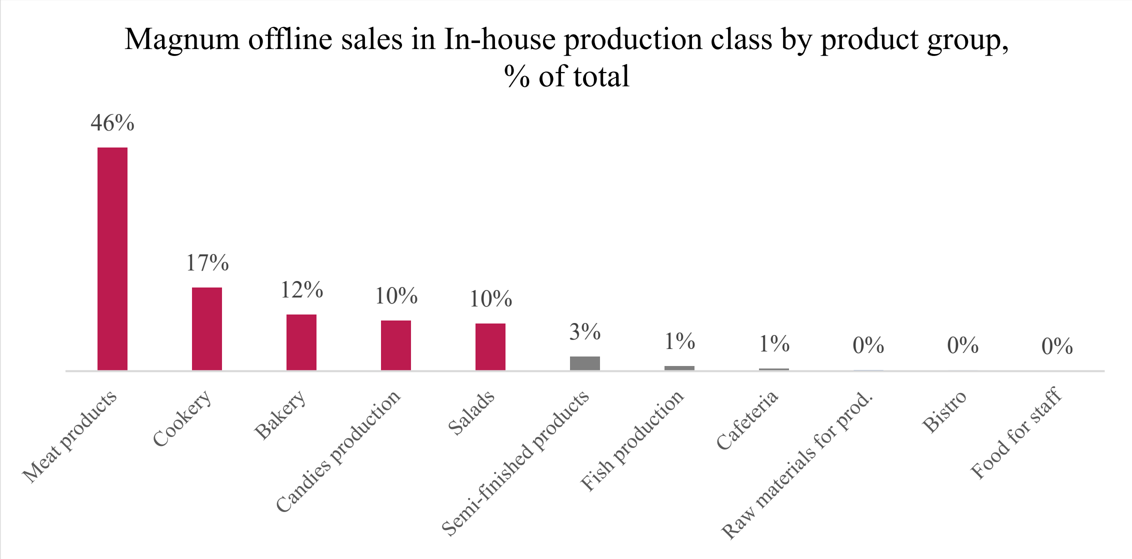


Figure 4.1.7. Magnum offline sales in the In-house production class by product group

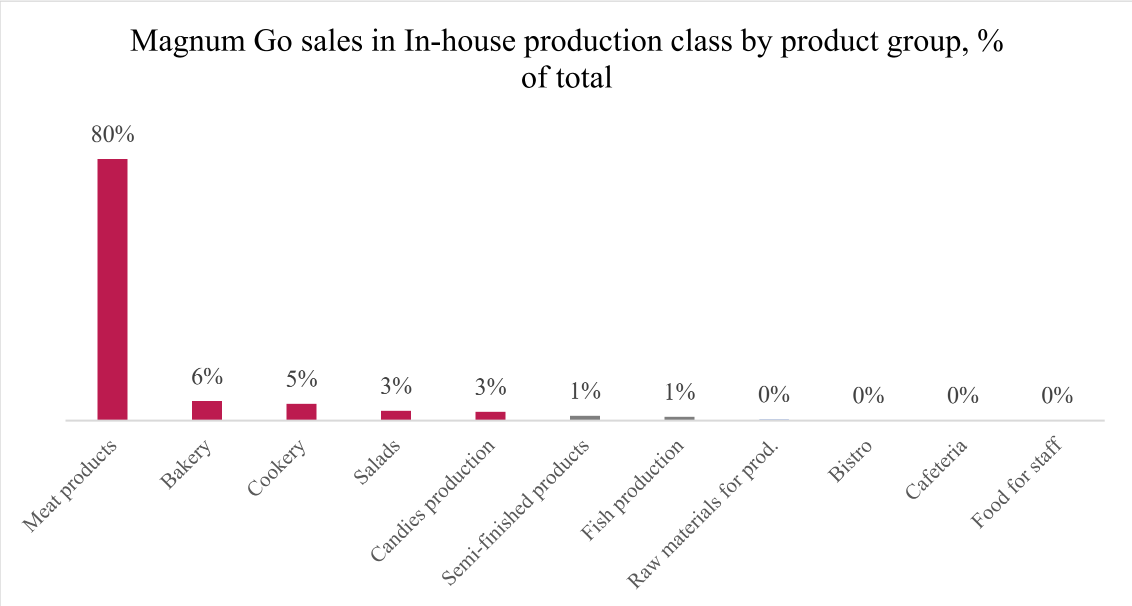


Figure 4.1.8. Magnum Go sales in the In-house production class by product group

To conclude with this part of the analysis, despite some similarities in the preferences of Magnum's offline and online users, their customer behaviours from the perspective of product classes and groups in each of the classes differ. These differences should be taken into consideration while refining the product assortment of the Magnum Go goods delivery service.

4.1.3. Comparison of average basket compositions

In this part of the report, the customer preferences of Magnum’s offline and online clients are analysed from another perspective. The Figures 4.1.9. and 4.1.10 represent the basket compositions of an average offline purchase and an average online order, respectively. It can be seen from the charts that the top-nine product groups of the average offline and online baskets have several common groups such as Dairy products, Pantry staples, Eggs, cheese and sausages, and others. However, the proportions of these product groups in average offline and online purchases are different. Besides, a couple of product groups do not appear on both charts, which are Frozen products and Meat products. Therefore, it can be concluded that despite some existing similarities in the charts, the customer preferences of Magnum’s offline and online users from the perspective of an average basket composition can be considered distinct.

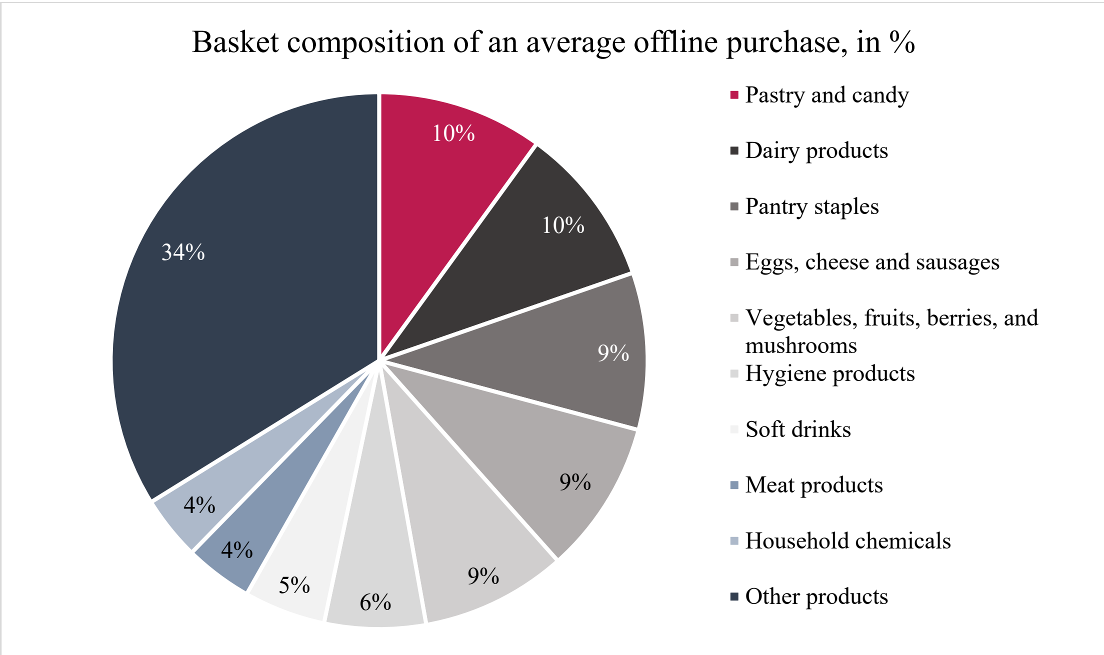


Figure 4.1.9. Basket composition of an average offline purchase

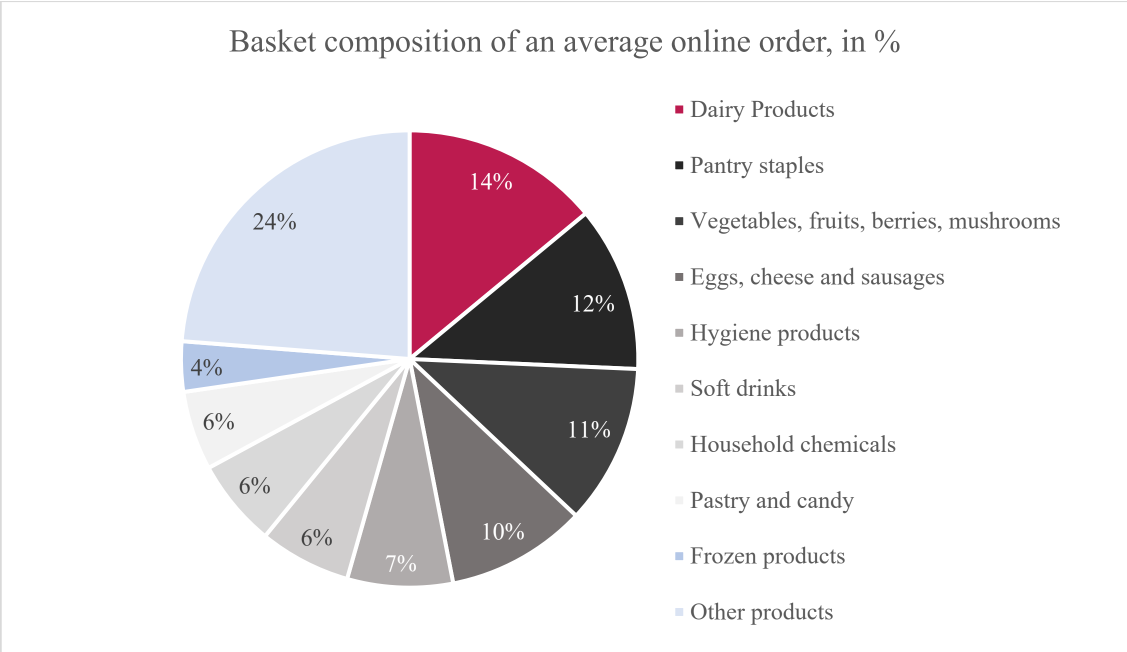


Figure 4.1.10. Basket composition of an average online order

4.1.4. Comparison in terms of weekdays and cities

This section of the report will present Magnum's offline and online sales analysis results with a breakdown of the days of the week (Figures 4.1.11 and 4.1.12). It can be easily noticed from both charts that the offline and online sales more or less remain the same during the week. The exceptions take place only on Saturday for offline sales and Wednesday for online ones. As for offline sales, it can be easily understood that, in general, Saturday can be considered the most popular day of the week for visiting stores and buying needed products. As for online sales, it can be noticed that no sales increases happened during the weekends. This is mainly due to the fact that online users do not depend on any days of the week to shop. The peak sales happening on Wednesday can be explained by the fact that December 30, 2020, New Year's Eve, fell on Wednesday. To sum up, what can be learned from the presented graphs is that although generally, the consumer behaviour of offline and online users during the week does not change, it differs during the weekend, especially on Saturday. The obtained insights can be considered quite important and helpful because they allow the company's managers to effectively plan and store the needed supplies and the human resources based on the day of the week and city.

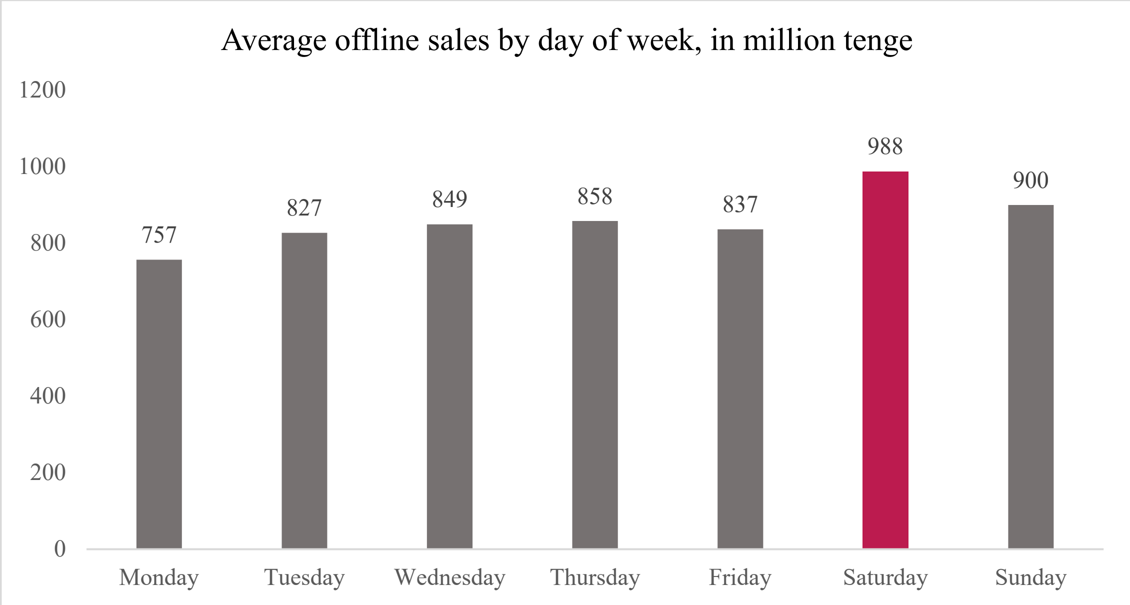


Figure 4.1.11. Average offline sales by day of the week, in a million tenge

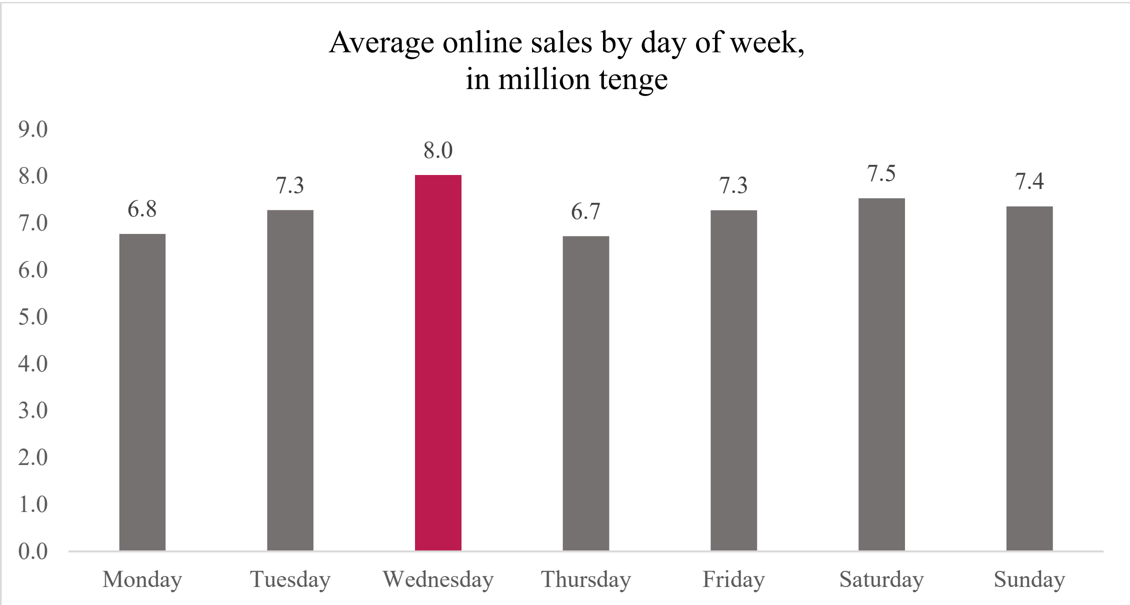


Figure 4.1.12. Average online sales by day of the week, in a million tenge

The following pie charts represent the overall distribution of Magnum's offline and online sales broken down into cities. From Figure 4.1.13, it can be observed that Almaty represents the leading city for offline sales, followed by Nur-Sultan, Shymkent, and other cities. A similar pattern appears to be for the Magnum Go sales. However, in this case, the proportion of sales in Almaty in the total sales volume is even higher and amounts to 73% (Figure 4.1.14). The derived insights are essential and will help Magnum's managers to effectively manage the company's warehouses, supplies, and human resources in order to meet the demand of online clients.

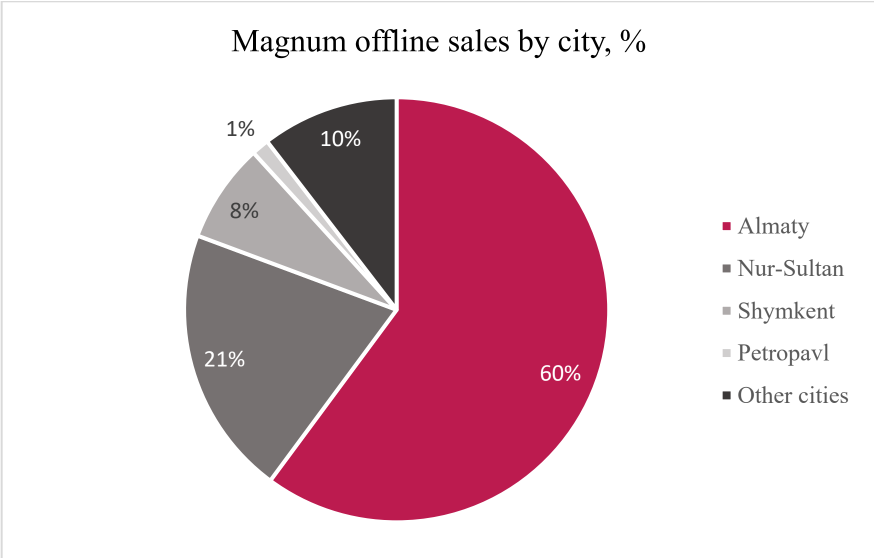


Figure 4.1.13. Magnum offline sales by city.

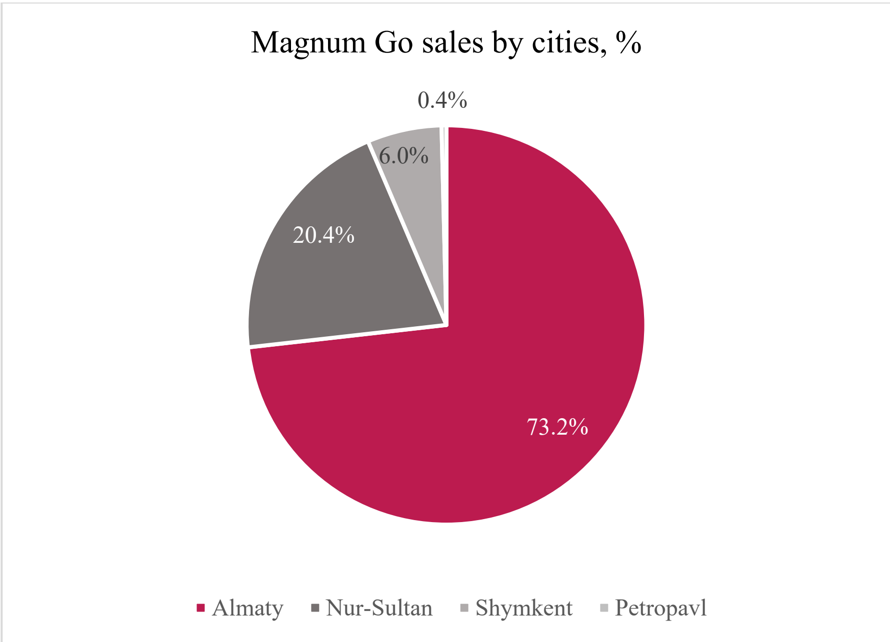


Figure 4.1.14. Magnum Go sales by city.

4.1.5. Summary of analysis

In conclusion, in this part of the report, Magnum's offline and online sales were analysed and compared. The primary purpose of this comparison was to identify any existing differences in preferences of offline and online consumers. The results of this analysis demonstrate that despite some observed similarities, Magnum's offline and online users have distinct customer preferences in terms of product classes, product groups in each of the classes, and an average basket composition. Besides, their consumer behaviours during the week have some differences as well. In other words, the hypothesis proposed at the beginning of this section can be accepted. Therefore, based on the derived insights, it can be concluded that the product assortments for offline and online users should differ as well. Next, for building a successful product assortment strategy for the Magnum Go channel, competitor analysis and benchmarking should be performed.

4.2. Competitors' assortment analysis

4.2.1. Analysis of product classes

One of the final deliverables of this project is to propose the new assortment for the Magnum Go e-commerce store. As stated in the literature review, one of the methods of assortment framing is the competitors' assortment analysis (Besbes and Sauré, 2016). This paper considers the leading Russian retailers such as Perekrestok, Utkonos, and Lenta (mobile app – Lentochka) for benchmarking purposes. The reason behind this choice is that the Russian FMCG retail e-commerce market is more established and has more significant players than the local market (Kursiv.kz, 2020). However, the analogous customer behaviour due to the similarities in people's mentality allows predicting related market patterns. As for the local competitor, the representatives of Magnum suggested considering Arbuz.kz, which is the online groceries delivery service in Almaty and Nur-Sultan.

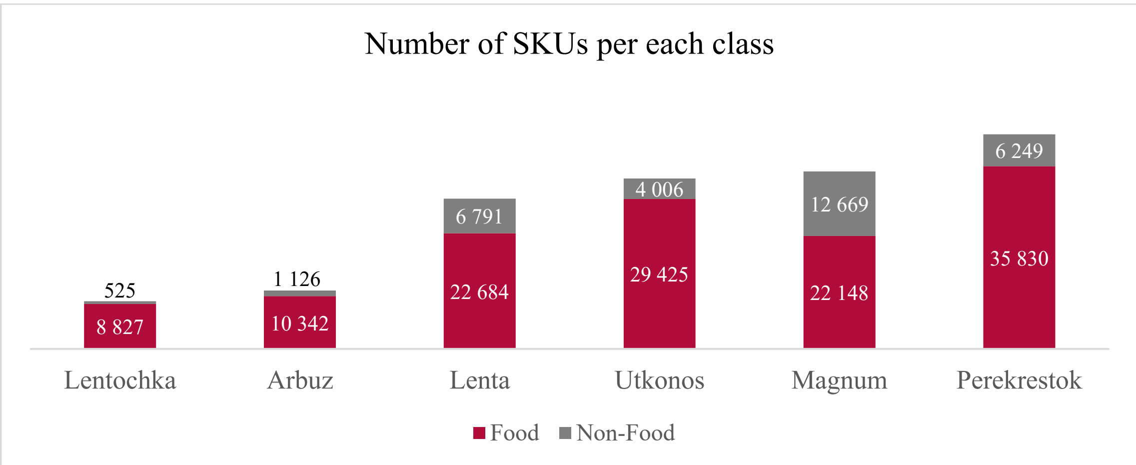


Figure 4.2.1a. Comparison of Magnum Go assortments with grocery delivery services in Kazakhstan and Russia

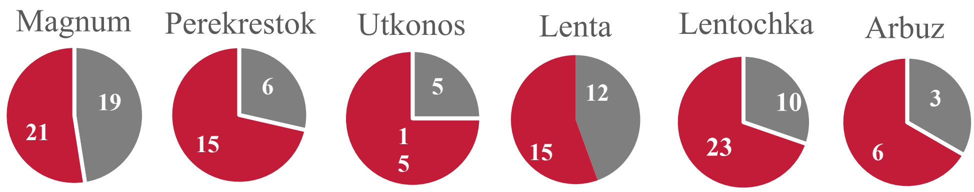


Figure 4.2.1b. Comparison of number of groups per each product class

The results of the manual collection of assortment data were compared at the different classification levels to construct the comprehensive analysis. Figure 4.2.1a indicates the total number of SKUs and the shares of Food and Non-Food classes of products in Magnum Go, leading Russian retailers, and local Arbuz.kz. In-house production, including ready meals, bakery products, salads, and cakes, was not compared at this stage since the competitors do not offer it. According to the results, the Perekrestok website provides the highest assortment range for its customers, while Magnum is the second-highest e-commerce platform among analysed stores. Besides, the chart reveals that the share of Non-Food products is the greatest in Magnum Go compared to other platforms. The average Non-Food items share of the competitors is about 13%; thus, the value in Magnum Go exceeds the average by 23%. This feature can be a competitive advantage for the company if these products bring value in terms of sales, profit margin, and strategic fit. Besides, Figure 4.2.1b shows that the number of groups in Food and Non-food classes are almost equal in Magnum, close to each other in Lenta, and Food width considerably exceeds Non-food in other stores.

Another point to mention is that the Russian retail chain Lenta has a mobile app with a different name, Lentochka, which has a smaller assortment size. According to Ganzhur (2020), the owners of Lenta stores started the e-commerce business by launching the mobile app for express delivery services and new product testing purposes. After one year, they also initiated an online ordering through their website. Thus, at the competitors' level of Food and Non-Food products, the differences in the assortment size, classes share, and e-commerce business format features were analysed.

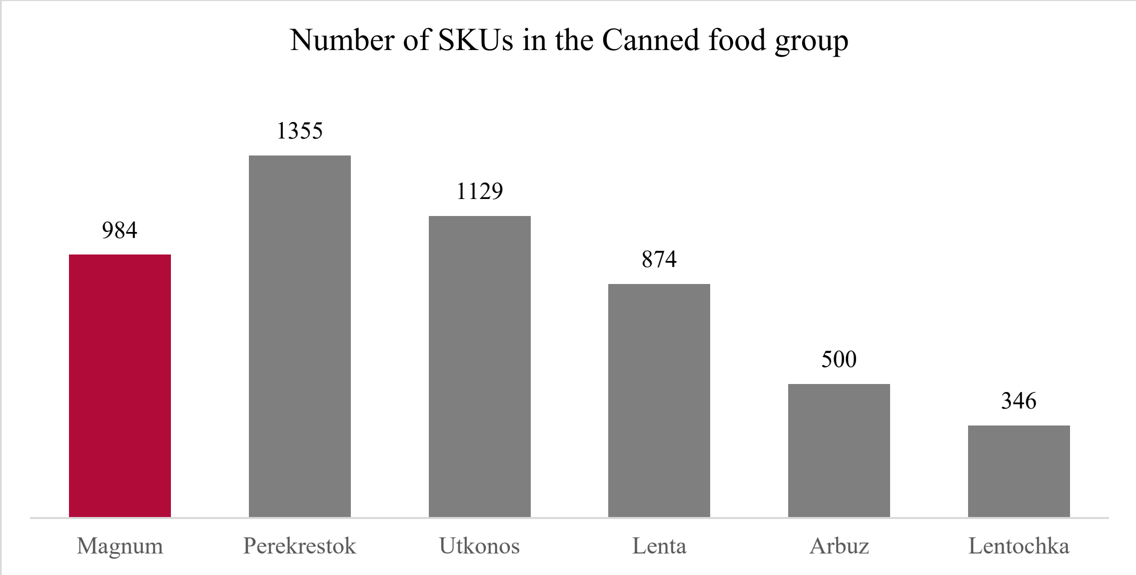
4.2.2. Analysis of product categories

Further investigation about the competitors' assortment of Food and Non-Food products required counting out the number of SKUs in each class group. Appendix 1 shows the distribution of items by groups in the class of Food products. According to the chart, the group of “Pantry staples” has the highest assortment depth in Magnum Go, Utkonos, and Arbuz stores. Besides, it is in the top five groups in the other analysed platforms. Despite the triple prevalence of Magnum Go over Arbuz.kz in the total assortment size, the amount of groceries in the local e-commerce competitor of Magnum is only about 14% lower. Overall, the groups such as “Cosmetics”, “Hygiene products”, “Pastry and candies”, and “Eggs, cheese, and sausages” appear in the top five in five out of six companies. Coming to the least diverse groups, most frequently they are “Alcohol drinks” and “Tobacco products”. The legal age restriction to these products and difficulties in controlling their sales during online purchases can explain this.

Magnum Go offers a considerably higher number of SKUs in the Non-Food class of products than other analysed companies. Appendix 2 depicts the assortment depth in each of the class's groups. “Household products”, “Goods for kids”, “Stationery products”, “Hosiery and tights” are the groups with the highest number of products among the six e-commerce platforms. We can notice that “Clothing” and “Footwear” are offered in a very small variety or even not presented in some of the stores, while in Magnum Go the quantities of SKUs in these groups are 159 and 236, respectively. Thus, this analysis showed the distribution of assortment size among the classes and groups of products and allowed comparing and contrasting the assortment depth in Magnum Go and some of its local and Russian competitors.

4.2.3. Analysis of product subcategories

After reviewing the similarities and differences in the upper levels of classification, a more detailed analysis of each group was performed. The competitors’ assortment analysis also provides an opportunity to compare the shares of different categories by the number of SKUs in each group. Figure 4.2.2. represents the distribution of SKUs into categories in the Canned food group. Each product category of Canned food on the Magnum Go e-commerce platform can be compared to the competitors’ assortment division. For example, Canned vegetables are the most diverse category, with 40% out of the group’s total on Magnum Go and an average value of about 43% on the competitors’ platforms. While these values are relatively similar, the share of “Canned fruits and berries” is about two times lower on Magnum Go than other considered e-commerce platforms. A similar comparison analysis was performed by using the data for all 40 groups. The obtained results may contribute to the decision-making on the addition or removal of particular product categories.



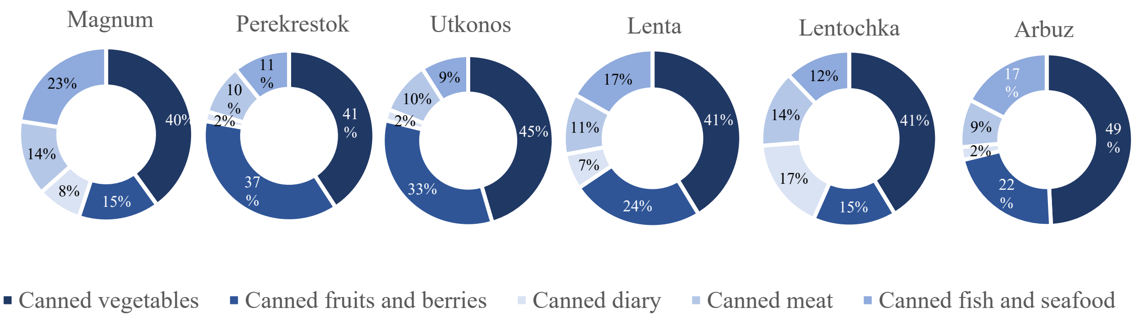


Figure 4.2.2. Distribution of SKUs in Canned food group of products

4.2.4. Analysis of competitors' categorisation and listing

Another valuable insight that can be derived from the competitor's analysis is their categorisation and listing features. The average number of groups in competitors' assortment is 22 with about nine categories and an assortment size of 25 000 SKUs; therefore, there are near 1100 items in each group. Mainly, products in the assortment of analysed e-commerce businesses are categorised based on similar nutritional properties, obtaining them in nature, and purpose of utilization. For example, pasta and grains have identical applications, and they are usually met in one group. The other common examples of groups that were often observed in the competitors are “Fruits and vegetables”, “Meat and fish”, “Frozen products”, and “Household products”. Another overall observation is that competitors mainly avoided the general naming of the group. Usually, the names explicitly stated what the customer should expect in a particular group or category. In general, each group consists of several product categories that represent a narrower set of products. In most of the competitors' platforms, all the categories were divided into subcategories; however, on Magnum Go, the last level of classification was sometimes missed. Overall, it was more convenient and practical when all the categories had a certain number of subcategories to allow an adequate representation of assortment.

In an e-commerce business, a listing of the assortment categories is critical. Based on the analysis of the Russian retailers and Arbuz.kz platforms, the main listing feature is that all the groups of Food class of products are listed before the Non-Food class. At the beginning of the listing, there are usually promotional goods, and the top five groups of products are “Fruits and vegetables”, “Dairy”, “Meat”, “Fish”, and “Bakery”. In contrast, towards the end of the catalogue, the “Automotive products” and “Sports goods” and “Goods for pets” are positioned.

4.2.5. Summary of competitors’ analysis

The assortment analysis of the competitors allowed a comparison of the number of SKUs in the different classification levels, including classes, groups, and categories. The results showed that Magnum has a considerably higher share of Non-Food items in its assortment than other stores. As for the Food class, despite some similarities in the top five groups, since the Russian retailers have more experience in e-commerce, they have a greater assortment width, and local companies can use their assortment as a benchmark. Next, the analysis of categories provided an overview of the distribution of SKUs in each product category of the groups. This information may contribute to the decision making on assortment depth and the content of the groups. Finally, the features and patterns of categorisation and listing on the competitors’ platforms were determined.

4.3. Categorisation and listing analysis

A competitor analysis gave an overview of the assortment that suitable for e-commerce platforms. Additionally, analysis of competitors' mobile apps and websites resulted in the in-depth examination of categorisation naming and product listing principles. These insights, coupled with the online customer needs found in the first paragraph, created a solid analytical foundation for forming a new assortment for Magnum Go. Therefore, the following section describes the new product assortment, which is more suitable for e-commerce platform, and the approach taken in building it. This part shows an improved categorisation naming that aimed to provide a more convenient and intuitive user experience. Finally, this paragraph presents an enhanced listing algorithm based on the product's sales, profit, and popularity among customers.

4.3.1. New categorisation

As a first step of adapting the existing assortment to the Magnum Go platform, the current categorisation of products has been examined. The following table illustrates an overview of the examination of the company's categorisation of products into classes and groups. The categorisation divides products into two distinct product classes: Food and Non-food. These classes have 21 and 19 product groups, respectively. However, some of the product groups that cannot be classified as food products are categorised into the Food class. These groups are "Household chemicals", "Goods for pets", "Cosmetics, perfume, pharmaceutics", "Hygiene products", and "Household goods". Their presence in the Food class creates confusion among customers of the e-commerce service. In addition, the sequence of groups is not consistent. The categorisation theory described in the literature review suggests grouping products in an associative manner. In other words, goods usually associated with each other should be placed close in a sequence of groups. For example, all alcohol drink-related groups should be placed together. However, in the existing categorisation "Elite alcohol" group is separated from other groups of alcohol products such as "Strong alcohol", "Wine", and "Beer and light alcohol drinks". Apart from that, the current sequence of the products is not ordered following the frequency of purchasing among customers. Generally, product groups that customers regularly purchase, such as dairy products, vegetables, and fruits, are placed at the beginning of the list for customer convenience. Unfortunately, in the current categorisation, frequently selling product groups are not placed higher in the sequence of groups.

Table 4.3.1. Current categorisation of Magnum's assortment

Class	Code	Group
Food	F01	Canned Goods
	F02	Pantry Staples
	F03	Baby Food
	F04	Pastry and Candy
	F05	Tea, Coffee, Cocoa
	F06	Strong Alcohol
	F07	Wine
	F08	Beer and Light Alcohol Drinks
	F09	Soft Drinks
	F10	Tobacco Products
	F11	Bread and Bakery
	F12	Eggs, Cheese, Sausages
	F13	Dairy Products
	F14	Frozen Products
	F15	Vegetables, Fruits, Berries, Mushrooms
	F16	Household Chemicals
	F17	Goods for Pets
	F18	Cosmetics, Perfume, Pharmaceutics
	F19	Hygiene Products
	F20	Household Goods
	F21	Elite Alcohol
Non-Food	NF01	Home Textile
	NF02	Household Products
	NF03	Party Supplies and Crafts
	NF04	Underwear
	NF05	Hosiery and Tights
	NF06	Clothing
	NF07	Footwear
	NF08	Accessories
	NF09	Entertainment Products
	NF10	Goods for Kids
	NF11	Stationery Products
	NF12	Sports Goods
	NF13	Tourism and Picnic
	NF14	Garden and Tools
	NF15	Bath, Sauna Products
	NF16	Goods for Car
	NF17	Electronics
	NF18	Household Appliances
	NF19	Do-it-yourself Products

Apart from those top-level issues with categorisation, there are also numerous problems inside many groups. In the next level of segmentation, each product groups have several categories. For instance, the "Wine" group has three distinct product categories: "Non-sparkling wine", "Sparkling wine", and "Special wine" (which includes fruit wines, vermouth, and liqueur wines). And each of these categories is further divided into subcategories based on the product characteristics. The complete categorisation of the group is illustrated in the table below.

Table 4.3.2. Full segmentation of the "Wine" product group

Code	Group	Category	Subcategory
F07	Wine	F0701 Non-sparkling wine	F070101 Red wine
F07	Wine	F0701 Non-sparkling wine	F070102 White wine
F07	Wine	F0701 Non-sparkling wine	F070103 Rosé
F07	Wine	F0702 Sparkling wine	F070201 Red sparkling wine
F07	Wine	F0702 Sparkling wine	F070202 White sparkling wine
F07	Wine	F0702 Sparkling wine	F070203 Other sparkling wine
F07	Wine	F0703 Special wine	F070301 Vermouth
F07	Wine	F0703 Special wine	F070302 Liqueur wine
F07	Wine	F0703 Special wine	F070301 Fruit wine
F07	Wine	F0703 Special wine	F070301 Other special wine

The further examination of assortment helped to identify additional problems on category and subcategory levels. One of the identified problems was misplaced categories. For example, in "Bear and light alcohol drinks" groups, among categories such as "Beer" and "Light alcohol drinks", there is a category name "Snacks". Although snacks are usually purchased with such beverages, it is not advised to cluster them into one group because of their disparate product characteristics. Also, competitor analysis showed that usually, in e-commerce platforms, these products are in different groups. In addition, since there is no mention of snacks in the group name, it hard for the customers to find the location of the snacks. Another problem on the category level is two quite similar categories placed in two different groups. For instance, a product category named "Pastries" includes biscuits, cupcakes, and other pastries. It categorised into the "Pastry and candy" group, which seems a very reasonable choice. However, there is also a category called "Frozen pastries", which includes frozen biscuits and cakes. This category is placed inside the "Bread and bakery" group. The literature review and competitor analysis suggest that such similar categories should not be separated into different product groups. Other competitors classify frozen pastries as a "Pastry and candy" group of products. Competitors' analysis identified another problem with Magnum's categorisation. It is an overgeneralised grouping of products. For example, the product group "Pantry staples" includes various product categories such as cooking oils, pasta, groats, sugar, baking flour, sauces, condiments, spices, instant foods, vinegar, and healthy food. In other e-commerce platforms, those product categories are grouped into several product groups and named accordingly so that the group name clearly states which categories are inside the group. Apart from that, the competitor analysis showed that many e-commerce platforms do not offer certain groups of products such as "Tobacco products". It seems like such products are not suitable for the needs of online buyers. It is proven by the analysis of Magnum Go sales, which indicated that for the period of four months, there were almost no sales in that category.

Since primary problems in the current categorisation of products were identified through consolidating competitor analysis and the analysis of Magnum offline and online sales, several changes in categorisation were made. Those changes include correcting generalised naming, restructuring groups and categories, and removing product groups that are not suitable for e-commerce. Firstly, the large product groups such as "Pantry staples" were restructured into several smaller groups and naming was changed from generalised titles to more specific names. The following table illustrates how the groups were restructured and how naming was altered. Dividing the "Pantry staples" group into several smaller groups helps the customer navigate easily since now, the name of each new group clearly describes what types of products can be found inside that group.

Additionally, the new groups were created based on the association theory of categorisation. For example, products in the "Pasta, groats, porridge" are usually used as side dishes in Kazakhstani cuisine. Unlike this group, product in the "Cooking oils, spices, and sauces are typically used with raw food during the meal preparation. Competitor analysis showed that such associative group forming makes navigation in the assortment easier for customers because they associate one type of products with another.

Table 4.3.3. The restructuring of the "Pantry staples" group

Old categorisation		**New categorisation**	
Group	Category	Group	Category
F02 Pantry Staples	F0201 Groats	Pasta, groats, porridge	Pasta
	F0202 Baking flour		Groats
	F0203 Pasta		Porridge and cereal
	F0204 Cereal, porridge	Flour and baking ingredients	Flour
	F0205 Cooking oils		Baking ingredients
	F0206 Sauces		Baking accessories
	F0207 Vinegars		Sugar
	F0208 Condiments, spices	Cooking oils, spices, and sauces	Cooking oils
	F0209 Sugar		Spices (including salt)
	F0210 Salt		Sauces and vinegars
	F0211 Extracts		Extracts
	F0212 Instant food	Instant food	
	F0213 Healthy food	Healthy food	

Secondly, the groups with products with disparate characteristics such as “Eggs, Cheese, Sausages” were reformed into different existing groups. Since cheese is classified as a dairy product, this category was moved to the “Dairy products” group. Customer usually tends to search dairy products for cheese both in offline and online stores. Apart from that, eggs were also added to the dairy product, and the group name was changed to “Dairy products and eggs”. It is because customer used to see these products placed together in the stores, and they have built a strong association between these products. Therefore, such restructuring helps to develop more straightforward and more intuitive navigation with the Magnum Go app. Thirdly, according to competitor analysis, the product groups that are not suitable for an online platform, such as “Tobacco products”, were removed from the assortment. The study of Magnum Go sales supports such a decision because some orders made for tobacco product are close to zero. Overall, all changes made in the categorisation of products were aimed to enhance customer experience by providing more effortless navigation.

4.3.2. New listing algorithm

After forming the new categorisation of assortment, further analysis was focused on developing an efficient product listing algorithm. It is crucial to have an optimal listing algorithm because it can improve customer experience and increase revenue and profit from sales. Showing the most popular products at the top of the list improves the user experience because the customer will spend less time on finding their favourite products. Unlike it, showing products with the highest profit margin may increase the overall profit from online sales; however, it might worsen the user experience. The present study, therefore, suggests a new listing algorithm that ranks the position of an item based on three indices: revenue, profit margin, and the number of orders in the last two months of sales. The following table illustrates the ranking of green tea based on the new listing algorithm.

Table 4.3.4. Ranking of green tea based the new listing algorithm.

SKU ID	Product name	Revenue	Revenue ranking	Orders	Orders ranking	Profit margin	Profit ranking	Average of rankings	Final ranking
354172	ЧАЙ GREENFIELD JASMINE DREAM	10 624	2	15	4	22%	11	6	1
288710	ЧАЙ GREENFIELD FLYING DRAGON	8 026	11	12	8	24%	1	7	2
288719	ЧАЙ GREENFIELD JASMINE DREAM	9 185	8	15	4	22%	11	8	3
360322	ЧАЙ GREENFIELD JASMINE DREAM	9 877	5	11	12	20%	20	12	4
572828	ЧАЙ GREENFIELD JASMINE DREAM	9 008	9	12	8	20%	20	12	4
593413	ЧАЙ GREENFIELD FLYING DRAGON	5 160	17	7	19	24%	1	12	4
290644	ЧАЙ ПРИНЦЕССА ЯВА КИТАЙСКИ	9 744	6	16	3	19%	31	13	7
288720	ЧАЙ GREENFIELD JASMINE DREAM	8 852	10	9	15	20%	20	15	8
364214	ЧАЙ GREENFIELD FLYING DRAGON	10 178	4	9	15	19%	33	17	9
398204	ЧАЙ GREENFIELD JASMINE DREAM	6 460	14	6	22	20%	20	19	10
288747	ЧАЙ TESS LIME ЗЕЛ ЦЕДРА ЦИТРУ	9 227	7	20	2	15%	48	19	11
359552	ЧАЙ AHMAD TEA КИТАЙСКИЙ ЗЕ	5 243	16	5	26	20%	17	20	12
572827	ЧАЙ GREENFIELD JASMINE DREAM	3 721	22	5	26	22%	11	20	12
288711	ЧАЙ GREENFIELD FLYING DRAGON	7 534	13	10	14	19%	33	20	14
392012	ЧАЙ GREENFIELD JASMINE DREAM	2 715	29	5	26	22%	11	22	15
295506	ЧАЙ PRINCESS JAVA ПРЕМИУМ УЛ	2 053	34	5	26	23%	6	22	15
572813	ЧАЙ GREENFIELD FLYING DRAGON	1 985	35	4	34	24%	1	23	17
360665	ЧАЙ TESS LIME ЗЕЛ ЦЕДРА ЦИТРУ	5 967	15	12	8	15%	48	24	18
293503	ЧАЙ ВАУСЕ ЗЕЛ #95-33 400ГР СТАБ	13 480	1	15	4	13%	70	25	19
403079	ЧАЙ GREENFIELD FLYING DRAGON	4 422	21	6	22	19%	33	25	20
359492	ЧАЙ ВАУСЕ ЗЕЛ 100ГР КОР	7 729	12	24	1	13%	65	26	21
374064	ЧАЙ GREENFIELD JASMINE DREAM	2 247	31	3	37	22%	11	26	22
389913	ЧАЙ ВАУСЕ ЗЕЛ #95-33 400ГР СТАБ	10 507	3	13	7	13%	70	27	23
540062	ЧАЙ GREENFIELD JASMINE DREAM	2 222	32	3	37	22%	11	27	23
288783	ЧАЙ ПИАЛА ЗЕЛ 100ГР КОР	3 398	24	8	17	15%	44	28	25
357840	ЧАЙ ПИАЛА ЗЕЛ 100ГР КОР	3 011	26	7	19	15%	44	30	26
461237	ЧАЙ PRINCESS JAVA ТРАДИЦИОНІ	2 881	28	12	8	15%	54	30	27
396082	ЧАЙ TESS LIME ЗЕЛ ЦЕДРА ЦИТРУ	3 029	25	7	19	15%	48	31	28
402984	ЧАЙ AHMAD TEA CHINESE ЗЕЛ ЛИ	2 072	33	4	34	20%	27	31	29
400275	ЧАЙ ВАУСЕ ЗЕЛ НАПИТОК ЗДОРО	4 427	20	8	17	13%	59	32	30
742324	ЧАЙ TIPSON ПРАЗДНИЧНАЯ КОЛЛ	4 857	19	3	37	17%	42	33	31
540048	ЧАЙ GREENFIELD FLYING DRAGON	1 212	49	2	48	24%	1	33	31
364843	ЧАЙ PRINCESS JAVA ПРЕМИУМ УЛ	942	55	3	37	23%	6	33	31
323024	ЧАЙ RICHARD ROYAL GREEN POLO	2 319	30	1	59	22%	10	33	34
288689	ЧАЙ ВАУСЕ ЗЕЛ 100ГР КОР	3 537	23	11	12	13%	65	33	35
288762	ЧАЙ АССАМ ЗЕЛ В/С ЛИСТ 100ГР К	1 895	37	5	26	18%	37	33	35
400021	ЧАЙ GREENFIELD FLYING DRAGON	1 159	51	2	48	24%	1	33	35
293008	ЧАЙ AHMAD TEA КИТАЙСКИЙ ЗЕ	1 978	36	2	48	20%	17	34	38
405251	ЧАЙ AHMAD TEA КИТАЙСКИЙ ЗЕ	1 870	38	2	48	20%	17	34	39
361299	ЧАЙ АССАМ ЗЕЛ В/С ЛИСТ 100ГР К	1 778	42	5	26	18%	37	35	40
357792	ЧАЙ ВАУСЕ ЗЕЛ #95-33 400ГР СТАБ	5 005	18	6	22	13%	70	37	41
540019	ЧАЙ ВАУСЕ ЗЕЛ НАПИТОК ЗДОРО	2 891	27	5	26	13%	59	37	42
404810	ЧАЙ PRINCESS JAVA ПРЕМИУМ УЛ	748	58	2	48	23%	6	37	42
541662	ЧАЙ PRINCESS JAVA ПРЕМИУМ УЛ	656	62	2	48	23%	6	39	44

Firstly, the algorithm ranks all SKUs based on their sales for the last two months (column revenue ranking). The product with the highest sales will be classified as the first, whereas the product with the least revenue will be ranked as the last. It will help to ensure that the most selling products will be displayed properly, which will facilitate sales even further. Secondly, the algorithm ranks all products in subcategory based on the number of orders in a similar manner of revenue ranking. It will help to enlist the most popular products among customers at the top of the list, simplifying navigation within the subcategory as more frequently selling product will be easier to find. Thirdly, products are ranked based on the profit margin. It will increase total profit from subcategory by ensuring that SKUs with high-profit margin are listed in higher positions. They will be more likely purchased by customers who are not loyal to certain products. After that, the average of three rankings is calculated to estimate the approximate position of the product based on the three different indices. The final ranking of each product is estimated based on that average. Overall, the present listing algorithm aims to increase the company's total profit while maintaining high efficacy of the satisfaction of customer needs.

4.3.3. Personalized listing algorithm

Apart from the product listing algorithm, this study also focuses on developing a personalized listing algorithm which will be used to identify product groups, categories, sub-categories, and product based on users' purchase history. The algorithm uses sales data on customer and, based on that, creates a list of the most suitable items for that customer while maintaining high-profit margins. The following table illustrates an example of product group sorting for one particular customer.

Table 4.3.5. Product group sorting based on personalised algorithm.

Client ID	Group	Number of orders	Orders ranking	Total sum of orders	Sum ranking	Avg. of Profit margin (%)	Profit ranking	Average ranking	Final ranking
77750717743	PASTRY AND CANDY	60	4	30328	2	20%	3	3	1
77750717743	PANTRY STAPLES	66	2	27802	3	15%	7	4	2
77750717743	DAIRY PRODUCTS	189	1	69815	1	7%	12	5	3
77750717743	HYGIENE PRODUCTS	44	5	17188	5	20%	4	5	3
77750717743	CANNED GOODS	7	8	2945	9	59%	1	6	5
77750717743	EGGS, CHEESE, SAUSAGES	15	7	25634	4	11%	9	7	6
77750717743	HOUSEHOLD GOODS	6	9	2195	10	23%	2	7	7
77750717743	VEGETABLES, FRUITS, BERI	65	3	16202	6	7%	13	7	8
77750717743	HOUSEHOLD CHEMICALS	15	6	16083	7	8%	11	8	9
77750717743	TEA, COFFEE, COCOA	4	10	1988	11	16%	6	9	10
77750717743	BEER AND LIGHT ALCOHOI	4	10	1546	12	18%	5	9	10
77750717743	COSMETICS, PERFUME, PHA	3	12	3087	8	14%	8	9	12
77750717743	TOBACCO PRODUCTS	1	13	539	13	10%	10	12	13
77750717743	BREAD & BAKERY	1	13	77	14	2%	14	14	14

As in the previous part, the personalised listing algorithm is based on three significant indices:

- the customer's number of purchases of products in different groups,
- the total sales of the customer, and
- the average profit margin of purchased products.

The algorithm ranks groups, categories, subcategories, and products based on these three parameters. After that, the program calculates an average ranking, which later will be used to determine the final ranking. This algorithm can improve customer experience by showing categories and subcategories which customer purchases more at the top of the list. Thus, mobile app users will not spend more time on finding categories, subcategories, and products that they purchase regularly. Since this algorithm is also used the profit margin of the product in the sorting decision, it increases the total profit from the e-commerce platform. A product with a high-profit margin will have higher chances to be placed at the top of the list. Apart from that, this algorithm can help create personalised promotional sales. Since the algorithm identifies the personalised list of items that particular customer like the most, the Magnum company can use this information to offer a promotional discount on such product, which will increase the size of the basket.

4.4. Mobile applications ergonomics analysis

The following part of the paper describes the calculations done to examine and compare UI and UX of different mobile applications for ordering grocery online, including Magnum Go. This study uses nine qualitative and three quantitative criteria in analysing web ergonomics of the mobile platforms. The criteria dimensions include functionality, aesthetics, information, and subjective quality. The analysis framework is based on the method presented in the paper by Stoyanov et al. (2015). However, the testing features irrelevant for the evaluation of mobile apps were initially removed. Table 4.4.1 represents the list of extracted criteria with descriptions that specify the features and details of the assessment. The selected criteria formed the basis of the questionnaire in which respondents were initially asked to download the apps and assess their UI/UX design elements.

Table 4.4.1. Mobile apps assessment criteria.

Dimension	Criteria	Description
Functionality	Performance	The speed of loading certain features is fast. No lagging or crashes during user activity
	Navigation	Intuitive navigation system without any friction
	Gestural design	Logical and useful mobile gestures (swipe, tap, long pressing etc). Optimal sizes of touch controls
Aesthetics	Graphics	The sizes, shapes and resolutions of icons or other items on app
	Layout	Functional and consistent layout of pages
	Visual appeal	Colours, fonts, overall visual balance of an app design
Information	Quality	Effective product description
	Quantity	Availability of a description for all products
	Visual	Availability of a corresponding picture for all products
Subjective quality	Worth recommendation	Would you recommend this app?
	Overall rating	What is your overall star rating of the app?

This part of the report will discuss the results of the User Experience tests conducted on the mobile applications of Magnum Go, Arbuz.kz, Lentochka, and Utkonos. The tests were performed in order to evaluate the Magnum Go mobile application in terms of User Experience and compare it with the mobile applications of the direct competitor and benchmark companies. Twenty SKUs were randomly selected for the testing. Three tests were carried out in total. The main purpose of the first test was to count the number of steps needed to be taken to find a particular product in the product catalogue of a mobile application. The results of the first test are presented in Table 4.4.2.

Table 4.4.2. Results of the Test 1.

		Number of steps needed to find a product in an application			
No.	Product Name	Magnum Go	Arbuz. kz	Lentochka	Utkonos
1	Potato, 3 kilos	33	7	6	6
2	Wash powder, Tide colour for washing machines	4	6	6	6
3	Shower gel, Nivea	4	4	6	6
4	Red bull energy drink	4	5	4	4
5	Drinking yoghurt, Danone	4	5	4	6
6	Packed rice	4	5	6	4
7	Apples, 2 kilos	22	8	7	5
8	Toothpaste, Colgate	4	4	6	6
9	Olive oil, ITLV	4	5	6	6
10	Dog food, Chappi	4	5	6	6
11	Fetaxa cheese	4	5	4	6
12	Snickers chocolate bar	4	5	4	6
13	Ahmad earl grey tea, bags	4	5	6	9
14	Pampers diapers	4	5	4	9
15	Calve mayonnaise	4	5	4	6
16	Pantene shampoo	4	5	6	9
17	Frozen puff yeast dough	4	5	6	10
18	Sunflower seeds	4	5	4	4
19	Barilla pasta	4	5	6	9
20	Cotton discs	4	5	6	6

The second test was performed with the purpose to identify the time required to find a particular product in the product catalogue of a mobile application and place it into the basket. The results of the test are presented in Table 4.4.3. The time is represented in seconds.

Table 4.4.3. Results of the Test 2.

		Time to find a product and place it into the basket, in seconds			
No.	Product Name	Magnum Go	Arbuz.kz	Lentochka	Utkonos
1	Potato, 3 kilos	18.50	11.8	12.12	18.70
2	Wash powder, Tide colour for washing machines	13.60	22.75	18.41	23.40
3	Shower gel, Nivea	13.55	31.45	22.55	27.26
4	Red bull energy drink	9.90	19.45	7.27	20.30
5	Drinking yoghurt, Danone	23.40	30.26	6.50	16.16
6	Packed rice	15.01	18.31	13.95	20.00
7	Apples, 2 kilos	27.95	15.7	17.66	16.31
8	Toothpaste, Colgate	23.30	15.76	13.36	19.15
9	Olive oil, ITLV	17.01	24.61	17.56	25.45
10	Dog food, Chappi	11.31	12.00	9.15	22.05
11	Fetaxa cheese	20.70	13.80	14.01	23.06
12	Snickers chocolate bar	12.90	15.95	7.96	18.56
13	Ahmad earl grey tea, bags	26.20	70.26	14.76	24.90
14	Pampers diapers	12.55	32.51	8.10	26.35
15	Calve mayonnaise	12.75	16.15	10.31	17.35
16	Pantene shampoo	15.30	36.26	11.25	24.86
17	Frozen puff yeast dough	15.40	18.15	12.16	20.66
18	Sunflower seeds	11.30	24.15	8.01	20.71
19	Barilla pasta	14.71	18.26	9.25	21.11
20	Cotton discs	14.61	11.25	11.51	18.31

Finally, the major reason to conduct the third test was to determine the total time required to find all twenty products in the product catalogue and place them in the basket. Results of the test are presented in Table 4.4.4.

Table 4.4.4. Results of the Test 3.

	Total time to make an order, in seconds
Magnum Go	323.65
Arbuz.kz	645.66
Lentochka	322.70
Utkonos	472.70

Qualitative assessment is based on the results of conducted survey. Points for each mobile app in each qualitative criterion (Ql_i) is calculated based on respondent choice of preference. In other words, if the app is respondent's first choice in navigation criterion, this app would be awarded four points. In a similar manner, if the app is the last choice, it would have only one point. In order to calculate the final points, the average of all respondents ($\bar{r}_i$) is calculated to conduct qualitative assessment. As for quantitative examination, the present study uses quantitative (Qn_i) indices obtained during the testing such as average time (in seconds) to make an order consisting of several items. Each criterion in both qualitative and quantitative part assigned weight (w_i), so that the sum of all weights is equal to one in each criteria group. Additionally, the final evaluation score (R_i) for each criterion is calculated by multiplication of weight and average score from respondents. The following table illustrates assessment criteria.

Table 4.4.5. Web ergonomic assessment criteria

Criteria	Importance	Evaluated score	Weighted score
Ql_1	w_1	$\underline{r}_1$	R_1
$\cdots$	$\cdots$	$\cdots$	$\cdots$
Ql_9	w_9	$\underline{r}_9$	R_9

The following table illustrates weight distribution of both quantitative and qualitative assessment criteria.

Table 4.4.6. Weight distribution of criteria

Assessment area (subtotal weight, in%)	**Criteria**	**Importance**
Functionality (25%)	Performance	4.17%
	Navigation	4.17%
	Gestural design	4.17%
	Test 1	4.17%
	Test 2	4.17%
	Test 3	4.17%
Aesthetics (25%)	Graphics	8.33%
	Layout	8.33%
	Visual appeal	8.33%
Information (25%)	Quality	8.33%
	Quantity	8.33%
	Visual of info	8.33%
Subjective quality (25%)	Worth recommending	12.5%
	Overall rating	12.5%
Total		**100%**

Based on the survey responds, the average score is each assessment area were calculated. The following figure depicts the results of the assessment. The results showed that Utkonos app is the absolute leader in all measurements. And Magnum Go, unfortunately, was rated lowest among these mobile apps. Therefore, it is suggested that the Magnum company will benchmark Utkonos app in improving Magnum Go. There should be significant development in each of assessment areas.

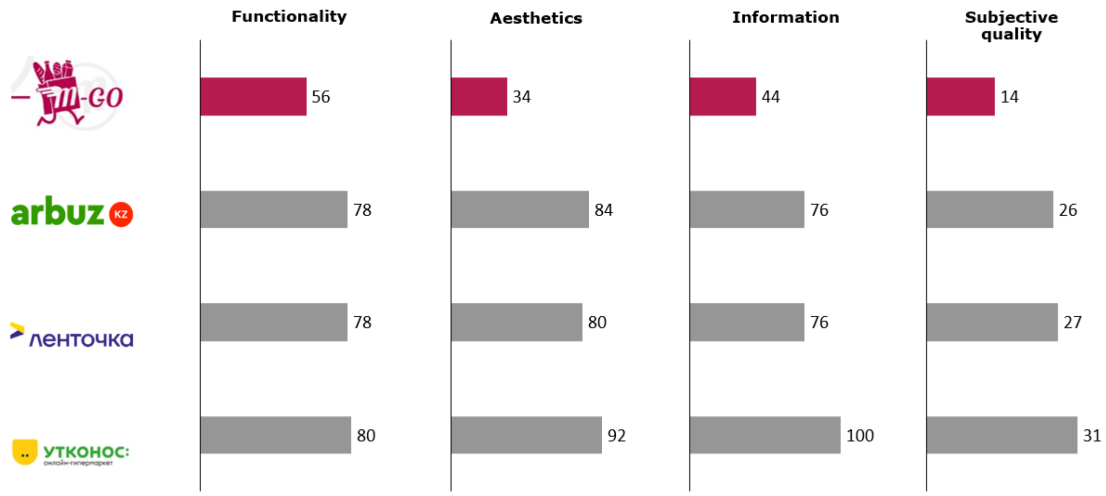


Figure 4.4.1. Results of the Survey Assessment

4.5. Interactive dashboard

One of the deliverables of the capstone project is building an interactive business dashboard. In Figure 4.5.1. an interactive dashboard for the Magnum Go sales analytics is presented. One of the most powerful and modern data analytics and visualisation tools, Tableau, was used to create this dashboard. At the top of the screen are dashboard cards representing the key performance indicators of the Magnum Go delivery service: Revenue, Number of orders, and an Average order rating. Below them are eight charts: a Map of Kazakhstan, Sales by Product Group, Sales by Product Category, Sales by Product Subcategory, Sales by Brand, Number of orders by day of the week, and Sales by Day and finally, Forecasting. The Map of Kazakhstan represents the four cities where Magnum Go operates: Almaty, Nur-Sultan, Shymkent, and Petropavl. The next three charts allow quick realising which of the product groups, categories and subcategories generate the most revenue. As for the Sales by Brand, this graph demonstrates the top-selling brands in a particular product group, category, or subcategory. The Number of orders by weekday chart represents how many orders were made on a particular weekday.

Next, the Sales by day chart demonstrates the sales volume each day. Finally, the Forecasting graph demonstrates the forecasted sales for the next four weeks. The sales forecasting is performed with the use of the exponential smoothing method. In all the eight presented graphs, features such as colour, size, and tooltips are used for a smarter visualisation and easiness of understanding the presented information. Moreover, the dashboard includes a variety of filters that are applied to all the presented transparencies. The Select Month filter allows viewing the Magnum Go sales performance by month. The Select Product Class filter enables viewing the sales by Food, Non-Food, or In-house production classes. Besides, the first four graphs are also used as filters which enable to view the sales performance for each specific city, product group, product category, and subcategory. In other words, Magnum Go's managers will have the opportunity to filter the sales data based on month, product class, city, product group, product category, and subcategory. Based on this dashboard, they will be able to plan their stocks and supplies, effectively manage their warehouses and human resources. In other words, they will have an opportunity to make well-informed and smart data-driven business decisions.

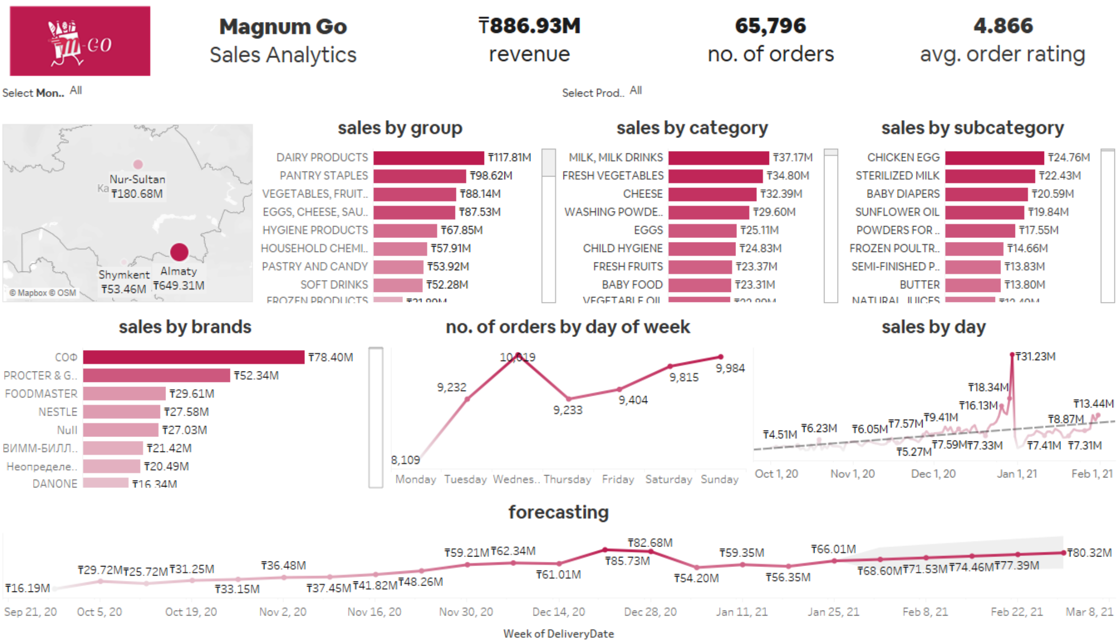


Figure 4.5.1. Magnum Go sales analytics interactive dashboard.

5. Conclusions and Guidelines for Future Research

The growing market share of e-commerce business has stimulated many companies to initiate online delivery channels, especially during the Covid-19 pandemic. Magnum Cash&Carry, as the largest FMCG retail chain in Kazakhstan, was not an exception. However, launching the Magnum Go e-commerce platform required additional operational and investment costs and the adoption of relevant assortment for the digital market. This paper focused on improving and adjusting Magnum's current assortment size to meet the needs of online buyers. The analysis was primarily based on BDA and relevant tools such as Microsoft Excel and Tableau.

The research framework comprised four main areas. The first was comparing offline and online sales in Magnum, which aimed to identify the different patterns in customers' preferences. The revealed discrepancies have proved that there is a need to adopt the new assortment for the e-commerce channel. The next step was conducting the competitors' analysis to assess the width and depth of the product assortment in Magnum Go, the local competitor Arbuz.kz, and the leading Russian retailers. The results showed that Magnum Go offers more variety of the Non-food class of products than the competitors. The findings from the first two parts were then used in designing the new categorisation and listing for the online delivery channel. Finally, the paper provided the assessment results of UI and UX efficiencies of Magnum's and considered competitors' mobile apps.

This paper offers the contributions to support the decisions of the company in the following ways:

- This study provides a comprehensive analytical foundation for improving the Magnum Go e-commerce channel. We have developed a systematic approach for the assortment adjustment based on the literature review, extensive sales analysis, and competitor analysis.
- Magnum can use the tools from this study to make data-driven strategic decisions. For example, an interactive dashboard allows assessing a company's performance and efficiently identifying the problem by filtering the relevant data and implementing real-time changes.
- Our work provides an overview of the assortment of leading Russian FMCG e-commerce retailers. The assortment width and depth

characteristics can be evaluated as an industry benchmark. Besides, the competitors' analysis allows identifying the features of product categorisation and listing.

- Another valuable contribution includes determining the significant areas of improvement for the Magnum Go mobile app. The company can use our findings of mobile app design and functionality KPIs for a better customer experience on a platform.

This project can be extended in a few ways. The provided dataset contained the information only for four months, including December, in which many holidays may deviate the results. More accurate investigations could be achieved with the data covering a more extended period. Besides, a broader dataset can improve the proposed forecasting model. This study also lacks data about customers demographics. Thus, another area of future research is to study customer profiles and preferences to stimulate Magnum to provide more personalised services on Magnum Go mobile app. Finally, the company can focus on the methods of synchronising offline and online channels and implement the omnichannel customer experience in which a customer journey is unified within the multiple channels.

6. References

Ahmad, Z. and Ibrahim, R., 2017. Mobile commerce (M-commerce) interface design: a review of literature. *OSR Journal of Computer Engineering (IOSR-JCE) e-ISSN,* pp.2278-0661.

Akter, S. and Wamba, S. F. (2016). Big data analytics in E-commerce: a systematic review and agenda for future research. *Electronic Markets*, *26*(2), 173-194.

Alfonso, V., Boar, C., Frost, J., Gambacorta, L. and Liu, J., 2021. E-commerce in the pandemic and beyond. BIS Bulletin, 36.

Ammar, A., Elouedi, Z., Lingras, P., 2016. Meta-clustering of 480 possibilistically segmented retail datasets. Fuzzy Sets and Systems 286, pp.173-196. doi:10.1016/j.fss.2015.07.019.

Analytical assortment optimization. Retail Analytics. 2019. [online] *McKinsey & Company*, pp.11-15. Available at: <https://www.mckinsey.com/~/media/mckinsey/industries/retail/how%20we%20help%20clients/big%20data%20and%20advanced%20analytics/mck_retail_analytics_brochure_v10.pdf> [Accessed 26 February 2021].

Ansari A. and Li, Y., Mizik, N., Hanssens, D. (Eds.), Big data analytics. Handbook of marketing analytics: Methods and applications in marketing management, public policy, and litigation support (2018), pp. 280-302

Arora A., Boudet J., Bucy M., Khan H., Montilla R., Smaje K. (2020). Think Fast: How to accelerate e-commerce growth. *McKinsey Digital*. [online] Available at:https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/think-fast-how-to-accelerate-e-commerce-growth# [Accessed 27 Feb. 2021].

Besbes, O. and Sauré, D., 2016. Product assortment and price competition under multinomial logit demand. *Production and Operations Management, 25(1),* pp.114-127.

Bhatti, A., Akram, H., Basit, H.M., Khan, A.U., Raza, S.M. and Naqvi, M.B., 2020. E-commerce trends during COVID-19 Pandemic. International Journal of Future Generation Communication and Networking, 13(2), pp.1449-1452.

Boysen, N., De Koster, R. and Weidinger, F., 2019. Warehousing in the e-commerce era: A survey. *European Journal of Operational Research, 277(2),* pp.396-411.

Bridger, R. S. (2018). *Introduction to Human Factors and Ergonomics*, 4th Edition. Boca Raton, FL, USA. CRC Press.

Broniarczyk, S.M. and Hoyer, W.D., 2006. Retail assortment: more≠ better. In *Retailing in the 21st Century* (pp. 225-238). Springer, Berlin, Heidelberg.

Colla, E. and Lapoule, P., 2012. E-commerce: Exploring the critical success factors. *International Journal of Retail & Distribution Management*.

de Souza, J.G., Kozielski, M., Mathur, P., Chang, E., Guerini, M., Negri, M., Turchi, M. and Matusov, E., 2018, November. Generating e-commerce product titles and predicting their quality. In *Proceedings of the 11th International Conference on Natural Language Generation* (pp. 233-243).

Díaz, J., Rusu, C. and Collazos, C.A., 2017. Experimental validation of a set of cultural-oriented usability heuristics: e-Commerce websites evaluation. *Computer Standards & Interfaces, 50,* pp.160-178.

Dillahunt, T.R., Simioni, S. and Xu, X., 2019, May. Online grocery delivery services: An opportunity to address food disparities in transportation-scarce areas. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1-15).

Dos Santos, V.F., Sabino, L.R., Morais, G.M. and Gonçalves, C.A., 2017. E-Commerce: A Short History Follow-up on Possible Trends. International Journal of Business Administration, 8(7), pp.130-138.

Einav, L., Levin, J., Popov, I. and Sundaresan, N., 2014. Growth, adoption, and use of mobile E-commerce. *American Economic Review, 104(5),* pp.489-94.

Flamand, T., Ghoniem, A., Haouari, M. and Maddah, B. (2018) Integrated assortment planning and store-wide shelf space allocation: An optimization-based approach. *Omega, 81,* 134–149.

Gandomi, A. and Haider, M. 2015. Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management, 35 (2)*, pp. 137-144.

Ganzhur, E., 2020. *Lenta launched online ordering of products through its own website.* [online] Forbes.ru. Available at: <https://www.forbes.ru/newsroom/biznes/396615-lenta-zapustila-onlayn-zakaz-produktov-cherez-sobstvennyy-sayt> [Accessed 10 April 2021].

Hart, C. and Rafiq, M., 2006. The dimensions of assortment: A proposed hierarchy of assortment decision making. *Int. Rev. of Retail, Distribution and Consumer Research, 16(3),* pp.333-351.

He, Y., Guo, X. and Chen, G., 2019. Assortment Size and Performance of Online Sellers: An Inverted U-Shaped Relationship. *Journal of the Association for Information Systems*, *20*(10), p.2.

He, Y., Guo, X. and Chen, G., 2019. Assortment Size and Performance of Online Sellers: An Inverted U-Shaped Relationship. *Journal of the Association for Information Systems, 20(10),* p.2.

Heese, H.S. and Martínez-de-Albéniz, V., 2018. Effects of assortment breadth announcements on manufacturer competition. *Manufacturing & Service Operations Management, 20(2),* pp.302-316.

Holý, V., Sokol, O. and Černý, M., 2017. Clustering retail products based on customer behaviour. *Applied Soft Computing, 60,* pp.752-762.

Jahanshahi, A.A., Mirzaie, A. and Asadollahi, A., 2011. Mobile commerce beyond electronic commerce: Issue and challenges. *Asian Journal of Business and Management Sciences, 1(2),* pp.119-129.

Karampatsa, M., Grigoroudis, E. and Matsatsinis, N.F., 2017. Retail category management: A review on assortment and shelf-space planning models. *Operational Research in Business and Economics,* pp.35-67.

Kim, R.Y., 2020. The impact of COVID-19 on consumers: Preparing for digital sales. IEEE Engineering Management Review, 48(3), pp.212-218.

Kök, A.G., Fisher, M.L. and Vaidyanathan, R., 2015. Assortment planning: Review of literature and industry practice. *Retail supply chain management,* pp.175-236.

Le, T. M. and Liaw, S. Y. (2017). Effects of pros and cons of applying big data analytics to consumers' responses in an e-commerce context. *Sustainability*, *9*(5), 798.

Lin, Z., 2014. An empirical investigation of user and system recommendations in e-commerce. *Decision Support Systems, 68,* pp.111-124.

Morton, E., 2017. More products lead to more growth in online retailing. *DigitalCommerce360.* [online] Available at: https://www.digitalcommerce360.com/2017/08/29/products-lead-growth-online-retailing/ [Accessed 05 Apr. 2021].

O'Raghallaigh, E., 2015. Security Issues in E-Commerce. *Digital Strategy.* [online] Available at: https://digitalstrategy.ie/security-issues-in-e-commerce/ [Accessed 04 Apr. 2021].

Oláh, J., Kitukutha, N., Haddad, H., Pakurár, M., Máté, D. and Popp, J., 2019. Achieving sustainable e-commerce in environmental, social and economic dimensions by taking possible trade-offs. Sustainability, 11(1), p.89.

Petrova, S., 2019. Determinants of choice of assortment size at a point of sale. *Trakia Journal of Sciences, 17(1),* pp.459-464.

Richardson, J., Schlegel, K., Sallam, R., Kronz, A., Sun, J. (2021). Magic Quadrant for Analytics and Business Intelligence Platforms. *Gartner.*

Ristoski, P., Petrovski, P., Mika, P. and Paulheim, H., 2018. A machine learning approach for product matching and categorization. *Semantic Web, 9(5),* pp.707-728.

Schmutz, P., Roth, S.P., Seckler, M. and Opwis, K., 2010. Designing product listing pages—Effects on sales and users' cognitive workload. *International journal of human-computer studies, 68(7),* pp.423-431.

Sd Kursiv.kz. 2020. *Why Kazakhstani retail does not welcome Russian chains.* [online] Available at: <https://kursiv.kz/news/kompanii/2020-12/pochemu-kazakhstanskiy-reteyl-ne-privetstvuet-rossiyskie-seti> [Accessed 10 April 2021].

Shao, X.F., 2020. Online and offline assortment strategy for vertically differentiated products. *IISE Transactions, 52(6),* pp.617-637.

Sharif, K., 2012. Impact of category management practices on customer satisfaction–Findings from Kuwaiti grocery retail sector. *Journal of Targeting, Measurement and Analysis for Marketing, 20(1),* pp.17-33.

Shorrock, S.T., Williams, C.A., 2016. Human factors and ergonomics methods in practice: three fundamental constraints. *Theor. Issues Ergon. Sci. 17,* 468–482.

Stoyanov, S.R., Hides, L., Kavanagh, D.J., Zelenko, O., Tjondronegoro, D. and Mani, M., 2015. Mobile app rating scale: a new tool for assessing the quality of health mobile apps. *JMIR mHealth and uHealth*, *3*(1), p.e27.

Sysoeva, S. and Buzukova, E., 2019. *Category management. Assortment management in retail.* 2nd ed. Saint Petersburg: Piter, pp.160-161.

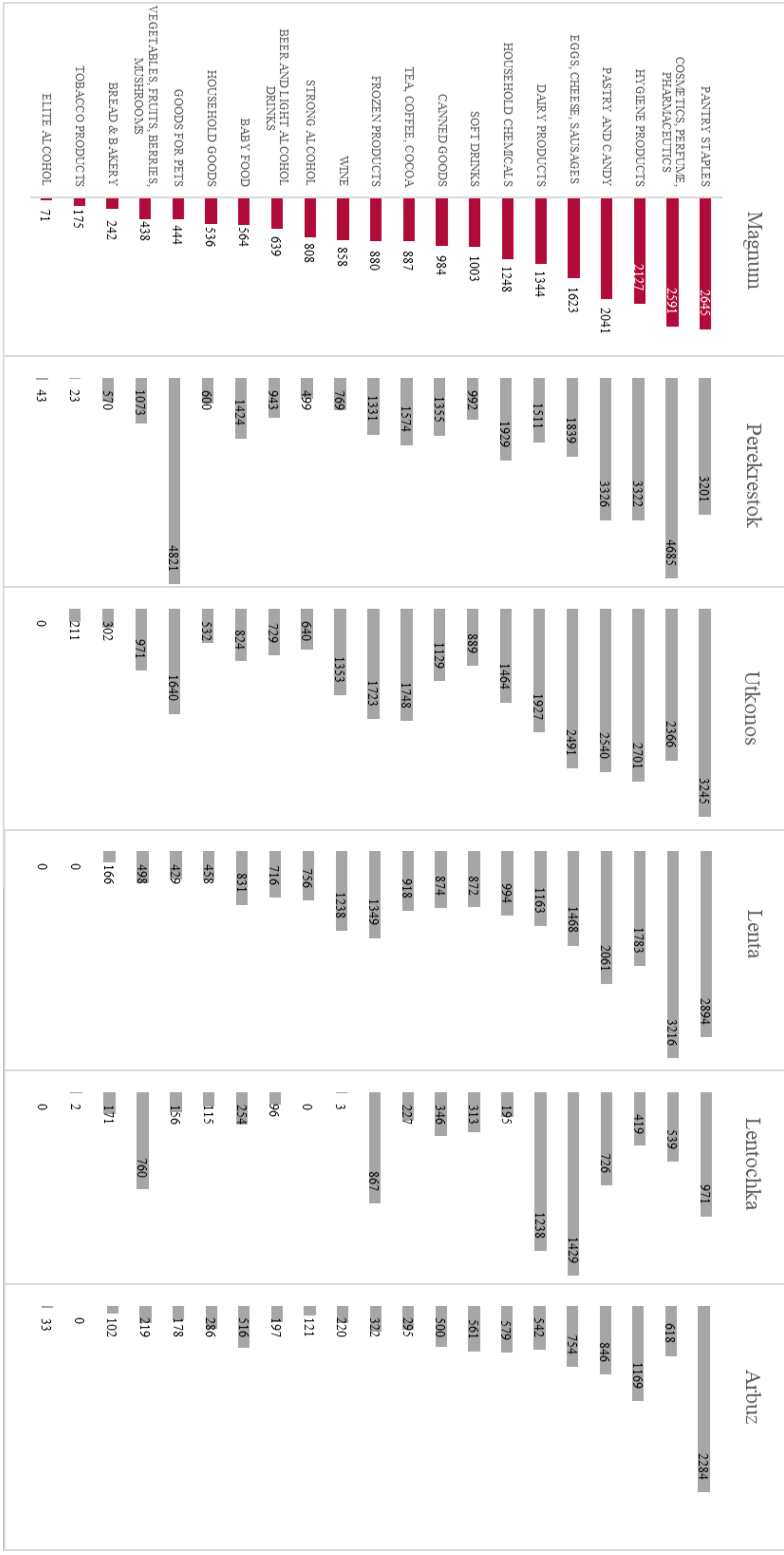
Uma, K., & Hanumanthappa, M., 2017. Data Collection Methods and Data Pre-processing Techniques for Healthcare Data Using Data Mining. *International Journal of Scientific & Engineering Research*, *8*(6), 1131-1136.

Van Der Heide, B., Johnson, B.K. and Vang, M.H., 2013. The effects of product photographs and reputation systems on consumer behavior and product cost on eBay. *Computers in Human Behavior, 29(3),* pp.570-576.

Wilson, J.R., 2014. Fundamentals of systems ergonomics/human factors. *Applied ergonomics, 45(1),* pp.5-13.

Zhang, Y., Jiao, J., Ma, Y., 2007. Market segmentation for product family positioning based on fuzzy clustering. *Journal of Engineering Design 18,* pp.227-241. doi:10.1080/09544820600752781.

Appendix 1. Competitors' assortment analysis: Food



Appendix 2. Competitors' assortment analysis: Non-Food