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Measuring Customer Experience based on Ecommerce Reviews: The Pedagogical case Study of LOOKFANTASTIC®

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Master in Management

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November 2022

BUSINESS
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Acknowledgments

Throughout the development of this thesis, I have received a lot of help,

I would first like to thank my supervisor, Professor João Vilas-Boas, not only for always being available to help and encourage me throughout the research process but also for passing me the passion for learning. His insightful feedback pushed me to sharpen my thinking and brought my work to a higher level.

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Finally, I am proud of myself for writing this thesis in a volatile environment. Nevertheless, I did not let that hold me back and I keep rising to the challenges. I am hoping that this work may be useful for future students in ecommerce and Marketing.

Abstract

User online reviews concerning Customer Experience are now part of the research agenda in marketing. Extant literature has mainly focused on classic survey-based approaches to accessing customer experience. However, online channels have become inevitable, and ecommerce practitioners should learn essential digital skills to get fresh customer insights.

This pedagogical case study was designed for practising innovative paths to investigate customer experience. Customer satisfaction and sentiment concerning Face Serums products were evaluated by both quantitative techniques such as Kruskal-Wallis H test and Ordinal Logistic Regression and text-mining techniques, e.g. Dictionary-based Sentiment Analysis applied to secondary data extracted from 361 numeric ratings and 5269 pieces of textual reviews posted in the online beauty shop LOOKFANTASTIC® (2011-2022).

The results show that customer satisfaction ratings significantly differ in ten Face Serums levels ranging from cheap to premium. This means that satisfying Face Serums are more likely to be found at a higher price according to a prediction index of product levels. Moreover, customer sentiment polarity and product attributes extracted from textual reviews mean that customers might feel more delight or dullness about some products, which might relate to attributes such as package, texture and smell.

This case study will teach the phenomenon fundamentals and their application to designing conceptual models. It will provide training to master students using digital skills, generating innovative insights to improve performance in Marketing, Product Development, and Customer Relationship Management. It also contributes to marketing and management literature by combining user-generated data such as numeric figures and narratives.

Keywords:

Customer Experience, online reviews, ecommerce

JEL Classification:

M300 Marketing and Advertising: General

M310 Marketing

Resumo

As avaliações online da Experiência do Cliente fazem agora parte da pesquisa em marketing. A literatura tem-se concentrado em abordagens clássicas, apesar da crescente importância dos canais *online* que geram necessidades de competências digitais para melhorar as perspectivas dos clientes.

Este estudo de caso pedagógico propõe alternativas para investigar a Experiência do Cliente. A Satisfação e o Sentimento do Cliente relativamente aos produtos *Face Serums* foram avaliados por técnicas quantitativas, como o teste Kruskal-Wallis H e a Regressão Logística Ordinal e, ainda por técnicas de *text mining*, como sejam a Análise de Sentimento Baseada em Dicionário, aplicados a dados secundários extraídos de 361 classificações numéricas e 5269 comentários postados no site LOOKFANTASTIC® (2011-2022).

Os resultados mostram índices de satisfação do cliente diferindo significativamente em dez níveis de *Face Serums*, variando de barato a premium. Os *Face Serums* satisfatórios são mais propensos a serem encontrados a um preço mais alto, de acordo com um índice de previsão. Também a polaridade do sentimento do cliente e os atributos do produto extraídos de análises textuais mostram que os clientes podem sentir mais ou menos prazer relativamente a alguns produtos, em função de atributos como a embalagem, textura e cheiro.

O caso explica os fundamentos do fenómeno e sua aplicação na concepção de modelos conceituais, facultando formação em competências digitais a alunos de mestrado, melhorando o desempenho em Marketing, Desenvolvimento de Produtos e Gestão do Relacionamento com o Cliente. Finalmente, contribui para a literatura de marketing/gestão, combinando dados numéricos e narrativas gerados pelo cliente.

Acronyms and Abbreviations

A - Assumption

ANOVA - Analysis of Variance

BK - Beer Karma

CS - Customer Satisfaction

CX - Customer Experience

E - Expectation

EDM - Expectancy-Disconfirmation Model

EP - Evaluated Performance

EXQ framework – Experience Quality framework

FMCG - Fast-Moving Consumer Goods

GHD - Good Hair Day

IBS - ISCTE Business School

IT - Information technology

KPC - Korea Cyber Payment

NLTK - Natural Language Toolkit

Q1 - Research Question 1

Q2 - Research Question 2

RRP - Recommended Retail Price

SEPA - Single Euro Payments Area

SQ - Service Quality

THG - The Hut Group

UK - United Kingdom

URL - Uniform Resource Locators

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Introduction

Nowadays, customer experience is receiving much attention in the scientific and managerial community (Johnston & Kong, 2011; Lemon & Verhoef, 2016; HAVÍŘ, 2017; Trischler et al., 2018) as it is considered a new direction in the area of marketing (HAVÍŘ, 2017). Customer experience is a distinct construct that comprises multidimensions during the purchasing journey (Lemon & Verhoef, 2016), thus it has been difficult to measure overall customer experience at a higher level. Nevertheless, extant literature focusing on specific components of customer experience has been developed and served as the building blocks in this field. Customer perception and customer sentiment, concerning the cognition and emotional components of overall customer experience (Lemon & Verhoef, 2016) respectively, have received special attention in academy.

Conventionally, customer perception and customer sentiment were measured by classic survey-based approaches, such as the SERVQUAL scale. However, these methods were argued to be insufficient in accessing these components (Gelbukh, 2017). On one hand, classic constructs are not comprehensible enough, and survey-based measurements of customers' perception and emotions might result in biases in customer insights and limit the breadth of understanding. On the other hand, traditional information collection methods being used in the survey are labour-intensive and time-consuming. With the rapid development of Internet technology, a large volume of customer reviews collected online open up the mind of researchers focusing on customer experience analysis and provide unprecedented opportunities to understand customer experience through user-generated content, which is free of bias than survey-based approaches (Chatterjee, Swagato, Divesh Goyal, Atul Prakash, 2020). More specifically in the ecommerce industry, which has seen rapid growth and concentrated various types of review data, the online rating is the comprehensible metric of customer satisfaction (e.g., Peng et al. 2019) which concerns the perception aspects of customer experience, and text review yields richer customer experience insights, the hottest of which is customer sentiments (Jagdale et al., 2019).

To fill the gap, a case of LOOKFANTASTIC® was considered. This is one of the largest European online beauty shops with a complete range of services and products that have been experienced and widely reviewed by its customers (*Lookfantastic International*, 2022). And the case study particularly focused on *Face Serums* (*Lookfantastic Face Serum*, 2022) available on this ecommerce website.

At the same time, digital skills are becoming more important in this era. Customer-facing functions, such as sales and marketing, which are more likely to act with reference to customer experience (Meyer & Andre, 2007), are facing the need to equip them with appropriate digital skills to leverage huge review data available online to yield customer experience insights that their decision might be based on. Thus, this case study is also developed with a pedagogical purpose.

With pedagogical purposes for training master students to gain customer experience insights based on online reviews, as referred to in §3.1, the author proposed two practical research questions that are relevant to customer experience and they were also designed to be the questions to be answered by students: (1) What is the association between customer satisfaction and the price levels of *Face Serums*, based on all current product ratings of *Face Serums*? (2) Can customer sentiments towards *Face Serums* at different levels be extracted from all current textual reviews of *Face Serums*? In this attempt, five research objectives were achieved to guide students step-by-step to the answers to the questions, as stated in §1.3. Throughout the journey of this pedagogical case study, a group of learning goals will be achieved and insights may contribute to specific business areas.

The structuring of this pedagogical case study from here on is as follows: Chapter 1 provides a case study of LOOKFANTASTIC®, specifically taking into account an introduction to *Face Serums* and the online review system, followed by the statement of research questions targeting *Face Serums*. Chapter 2 introduce the methodology applied by this thesis, which is the pedagogical case study. Chapter 3 covers all pedagogical notes, including the target audience, learning goals, literature review, animation plan, case resolution, and case study slides. Chapter 4 provides a discussion and conclusion.

1 Case Study

1.1 Problem Identification

Customer experience is considered a new direction in the area of marketing (HAVÍŘ, 2017). During a customer's entire purchase journey, customer experience is a multidimensional construct that focuses on a customer's cognitive, emotional, behavioral, sensorial, and social responses to a firm's offerings (e.g., product, service, and brands) (Lemon & Verhoef, 2016). Further, customer experience may even encompass every aspect of a company's offering, such as the quality of customer care, of course, but also advertising, packaging, product and service features, ease of use, and reliability (Meyer & Andre, 2007).

Given such a comprehensive scope of customer experience (Meyer & Andre, 2007) and the possibility to extract insights from online reviews (e.g., Ban & Kim, 2019), a pilot study was conducted to diagnose the issues of customer experience of *Face Serums* available on LOOKFANTASTIC® (*Lookfantastic International*, 2022) based on the customer reviews.

At a first sight, it was found that numeric rating and textual review are the two main types of reviews provided by the review system of LOOKFANTASTIC®. As shown in Figure 1.1**,** customers' sentiments could be recognized from the textual body of reviews, such as by words like "excited" and "happy".

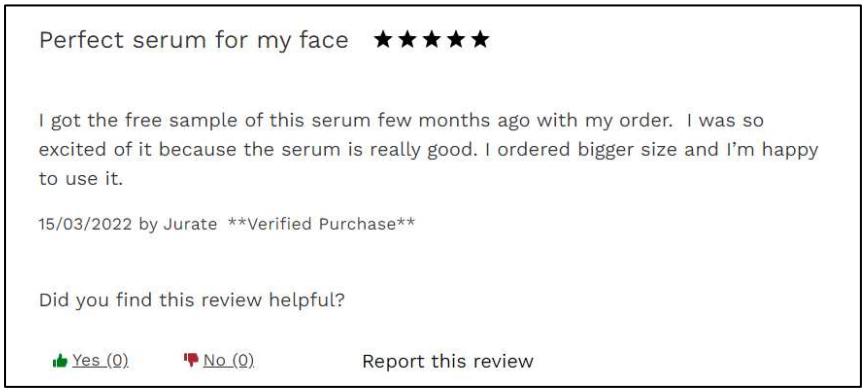


Figure 1.1 - A sample of the review

Source: Lookfantastic Product Details (2022)

Taking a deeper view, one might observe from a collection of product ratings in Table 1.1 that customers seem to have different degrees of satisfaction (Chatterjee et al., 2020) with expensive, medium, and affordable *Face Serums.* The average rating (4.78) of the first three higher-priced products from Shiseido, Estée Lauder, and Lancôme is relatively higher than that of the other two groups of Face serum (4.46 and 4.48).

Table 1.1 - A summary of the pilot study

Name	Price (€/30ml)	Number of reviews	Rating
Shiseido Ultimune Power Infusing Concentrate	67.95	47	4.85
Estée Lauder Advanced Night Repair Synchronized Multi-Recovery Complex Serum	67.95	160	4.79
Lancôme Advanced Génifique Youth Activating Serum	67.95	29	4.69
Average		78.67	**4.78**
Kiehl's Midnight Recovery Concentrate	46.45	26	4.85
La Roche-Posay Hyalu B5 Hyaluronic Acid Serum	42.95	55	4.69
La Roche-Posay Pure Vitamin C10 Serum	42.95	50	3.96
Caudalie Vinosource SOS Thirst Quenching Serum	32.95	56	4.74
Average		53.67	**4.46**
The Ordinary Caffeine Solution 5% + EGCG	13.45	344	4.55
The Ordinary Hyaluronic Acid 2% + B5 Hydration Support Formula	6.98	449	4.69
The Ordinary Niacinamide 10% + Zinc 1% High Strength Vitamin and Mineral Blemish Formula	5.95	185	4.21
Average		326.00	**4.48**

Source: Lookfantastic Face Serum List (2022)

This pilot study led to the formation of two research questions. In §1.3, these two research questions will be restated with specified research objectives, which guide students to insight into customer experience based on two types of ecommerce reviews. Nevertheless, before looking for the answers, it is necessary to get an overview of the core offerings of LOOKFANTASTIC®, *Face Serums* in particular. Further, as both types of online reviews will be used to provide customer insights, an introduction to the review system of LOOKFANTASTIC® will also be covered in the next section as well.

1.2 LOOKFANTASTIC®

1.2.1 History

In 1978, LOOKFANTASTIC® was born out of the Crown's Salon Group, a Sussex-based business that was well respected in the professional hair industry for both its traditional salon heritage and specialist training and education centers for hairdressers. The logo of LOOKFANTASTIC® was shown in Figure 1.2.



Figure 1.2 - LOOKFANTASTIC® logo

Source: Lookfantastic Archives (2022)

In 1997, LOOKFANTASTIC® aimed to move online to make high-end hair and beauty brands more accessible, with favorite brands plus professional product information available at the click of a mouse.

Over the years, the company has developed strong relationships with every professional hair brand in the industry, whilst beauty continues to grow at a rapid rate. In the summer of 2008, LOOKFANTASTIC® increased its offerings to include male grooming with the successful launch of Lookmantastic.com.

In 2010, LOOKFANTASTIC® was acquired by *THG Holdings plc,* a globally renowned end-to-end tech platform based in Northwich Cheshire and specializing in taking brands directly to consumers across the globe. *THG Holdings plc* used its proprietary technology and infrastructure to enable LOOKFANTASTIC® to grow at scale while driving unrivaled value and continuous performance: It has created *1 international site* and *over 29 localized sites* and in 2017 alone, it has attracted over 10 million visits per month; 71% of which were international. (*Lookfantastic International*, 2022)

Today, LOOKFANTASTIC® has grown to become Europe's number one online premium beauty retailer and even one of the most successful beauty websites globally. It carries, a portfolio of over 660 premium brands onsite, including *MAC, Kérastase, and Yves Saint Laurent, and* over 22,000 products with complimentary worldwide shipping to over 200 countries (*Lookfantastic International*, 2022).

LOOKFANTASTIC® is constantly adapting to and welcoming new trends in the industry. In the future, it will build a more luxury portfolio of partners with more clean, vegan, and organic beauty brands than ever before across skin, hair, and body care.

1.2.3 Core Offerings

LOOKFANTASTIC® offers both products and services, based on which online reviews are created by customers. In the first part of this section, special attention will be paid to *Skincare* products and more specifically, *Face Serums*. In the second half, four main types of services will be covered.

1.2.3.1 Products

(1) All Categories

Overall, LOOKFANTASTIC® International serves Beauty and Personal Care products covering seven main categories: *Skincare, Hair, Makeup, Body, Flagrance, Men, Wellness,* and *Tools.* The numbers of products in each category sold at LOOKFANTASTIC® International are shown in Table 1.2, where the *Skincare* category has the largest number of products.

Table 1.2 - All product categories on LOOKFANTASTIC®

Category	Number of Products	Percentage
Skincare	7558	27.99%
Makeup	6530	24.18%
Hair	4988	18.47%
Body	4077	15.10%
Men	1488	5.51%
Flagrance	1301	4.82%
Wellness	1064	3.94%
Total	27006	100.00%

Source: Lookfantastic International (2022)

(2) Skincare

Skincare on LOOKFANTASTIC® International site can be separated into 11 sub-categories listed in Table 1.3, among which *Moisturiser* has the largest number of products (2834) while *Serums* take the fourth place (1034). As there might be some overlaps among these sub-categories, the sum of the number of products within each sub-category exceeds 7558.

In terms of the *Serums* in *Skincare*, there are many alternative ways to name this sub-category, such as *concentrate, essence, essential liquid, intense, and spot corrector*. But all these names refer to the same type of products – "The lightweight products to be applied after

you cleanse and before you moisturize in the daily skincare routine that are formulated to maximize hydration and significantly improve your skin's complexion. They are an extremely valuable addition to the skincare regime." (*Lookfantastic International*, 2022).

According to the part of the body a *Serum* product should be applied to, *Serums* could be divided into *Eye Serum and Facial Serum.* The volume of *Eye Serums* is generally smaller than *Facial Serums* and the unit prices are generally higher. Figure 1.3 compared *Face Serum* with *Eye Serum* from the Japanese brand, *Shiseido*.

Table 1.3 - Sub-categories of Skincare

Sub-category	Number
Moisturiser	2834
Cleansers	1206
Face Masks	1060
Serums	1034
Toner	668
Eye Creams & Eye Care	631
Exfoliators	453
Lip Balms	435
Men's shaving	167
Micellar Water	112
Face Peels	63

Source: Lookfantastic International (2022)



Figure 1.3 - Face Serum VS Eye Serum

Source: Lookfantastic International (2022)

(3) Face Serum

Face Serum is the specific type of *Serum* that this pedagogical study focuses on.

Face Serums have been specially formulated to target different skin goals and to suit different skin types and conditions. For example, consumers can use a brightening *Face Serum* to illuminate their face or an *anti-imperfection* serum that reduces the appearance of *blemishes*

and *acne.* Whatever the skin type, one will be sure to find a *Face Serum* that suits her skincare needs in LOOKFANTASTIC®.

LOOKFANTASTIC® International provides 588 *Face Serums* from 180 *Skincare* brands in total. It could be observed in Figure 1.4 that most brands (66.38%) launched only one *Face Serum* product on LOOKFANTASTIC® International and nearly 90% of *Skincare* brands have no more than six *Face Serums* items.

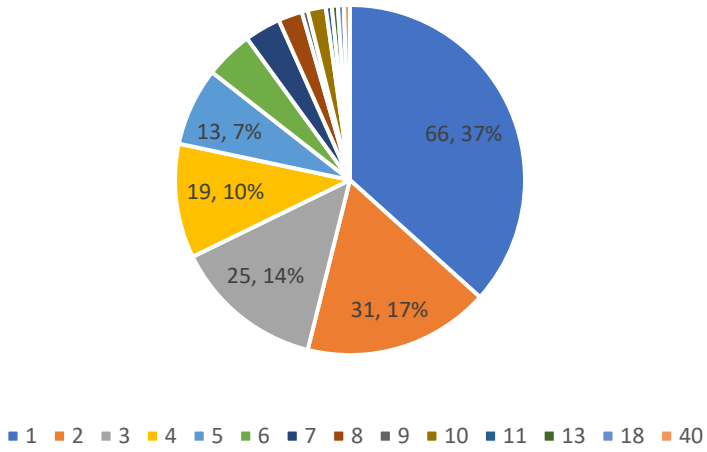


Figure 1.4 - Distribution of the number of Facial Serums

Source: Lookfantastic International (2022)

As shown in Table 1.4, The Ordinary is the brand with the largest amount of Face Serums. Moreover, Revolution, Medik8, Dermalogica, Clinique, Elizabeth Arden, and The INKEY are the brands with over ten Face Serums. While some brands aim to formulate Face Serums that targeted as many skin goals as possible, such as The Ordinary, most do not choose to launch too many similar items with the purpose of keeping the product line simpler.

Table 1.4 - Brands with the largest number of Facial Serums

Brands	Number of Facial Serums
The Ordinary	40
Revolution	18
Medik8	13
Dermalogica	11
Clinique	10
Elizabeth Arden	10
The INKEY	10

Source: Lookfantastic International (2022)

The prices of Face Serums available on LOOKFANTASTIC® International approximately range from around 5 euros to over 400 euros, one of the cheapest and the most expensive Face Serums is shown in Figure 1.5 LOOKFANTASTIC® has no specific preferences for the selection of premium Face Serums or affordable Face Serums, achieving good product diversification.

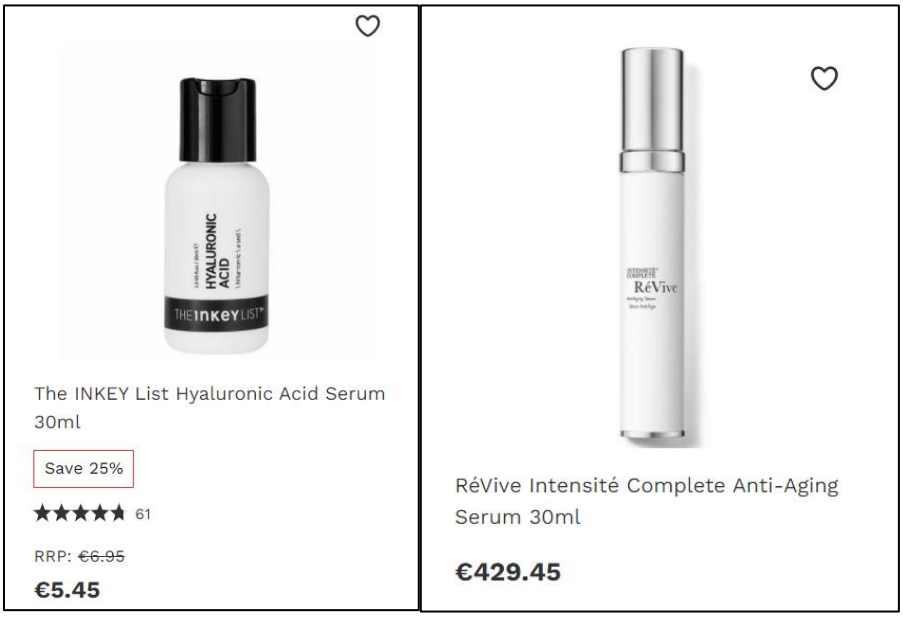


Figure 1.5 - The cheapest and the most expensive Face Serum

Source: Lookfantastic International (2022)

1.2.3.2 Services

LOOKFANTASTIC® provides four types of services to support the purchasing journey, notably including online payment, international delivery, returns & cancellation, and customer service.

(1) Payment Options

LOOKFANTASTIC® International supports 17 payment options, which are shown in Figure 1.6. Payment options are adapted to localized sites, such as *UnionPay* for Singapore and Japan, *KPC* for South Korea, *Single Euro Payments Area (SEPA)* for Greece, *AfterPay* for Poland, *Yandex,* and *WebMoney* for Russian.



Figure 1.6 - Payment options on LOOKFANTASTIC® International

Source: Lookfantastic International (2022)

In the portfolio of 28 payment methods on all sites of LOOKFANTASTIC®, *Visa, Mastercard, Maestro, American Express, Diners Club International,* and *Discover* are shared by all sites, as shown in Figure 1.7.



Figure 1.7 - Payment options shared by all sites

Source: Lookfantastic International (2022)

(2) Delivery Options

The types and prices of delivery options vary among the United Kingdom and other European destinations, as well as the rest of the world. For the destinations in UK, LOOKFANTASTIC® provides seven delivery options and the respective prices are shown in Table 1.5.

Table 1.5 - Delivery options for destinations in UK

Delivery options for UK	Price
Premier delivery	£ 9.9
Inpost locker & contact free delivery	£ 1.95 or free on order over £ 25
Tracked click & collect	£ 2.95 or free on order over £ 25
Tracked delivery	£ 3.95 or free on order over £ 25
Next day delivery	£ 4.95
Eco delivery	NA
Same day delivery	£ 13.9

Source: Lookfantastic International (2022)

While for other European destinations and the rest of the world, *Express delivery, Tracked delivery, Standard delivery, Worldwide express, and International standard delivery* are the main delivery options (*Lookfantastic*, 2022). Cyprus and Singapore are the European and non-

European countries to which products will be delivered within the longest delivery days, respectively up to 12 days and 15 days from the UK (*Lookfantastic International*, 2022). LOOKFANTASTIC® could guarantee the package delivered to most European countries within 1 week and the rest of the world within 2 weeks.

(3) Returns & Cancellation

Any damaged, faulty, or incorrect items that are within policy and in pristine condition could be returned (*Lookfantastic International*, 2022). Customers also have the right to cancel their contract within 14 days without giving a reason. Before attempting to return an order, the customer needs to contact the customer service team, who can be reached through the messaging center in LOOKFANTASTIC® International. But to report a fault with a *GHD product or L'Oreal Professionnel Steampod* product, customers have to contact the customer service team on third-party websites.

LOOKFANTASTIC® International will reimburse all payments received from the customers, including the cost of delivery. Meanwhile, it will refund postage costs to return an item where the return is required due to its error, but not which are unwanted or no longer required, or where no error was found in the testing process.

(4) Customer Service

Live chat is available on LOOKFANTASTIC® International site. When the tag is on the green, there will be a customer service representative available to serve you one-to-one. Customers can also choose to leave a supporting image or document that will assist the customer service representative with the query, for example, an image of a damaged item, through *Message.* All of these are shown in Figure 1.8.

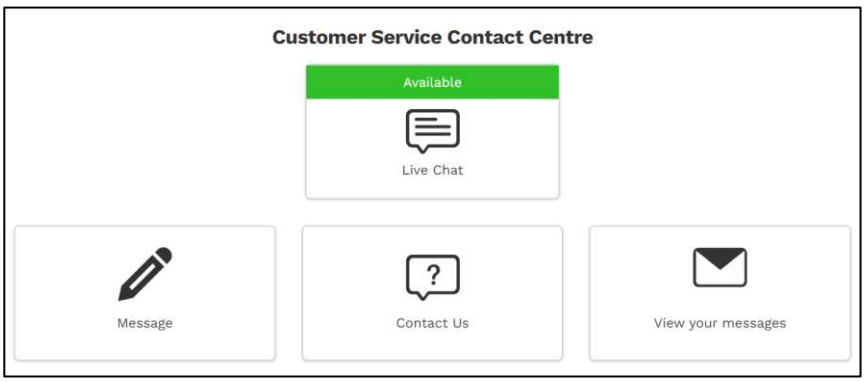


Figure 1.8 - Customer Service Options

Source: Lookfantastic International (2022)

1.2.4 Customer Reviews

Customer reviews can be presented at three places of LOOKFANTASTIC® International.

Firstly, as shown in Figure 1.9, at the bottom of a display image of each product, customers may find a rating star followed by the number of reviews. Other information, such as the *Recommended Retail Price (RRP)* and *the actual price*, is also provided nearby at the bottom of a display image of each product.



Figure 1.9 - Product reviews on the general page

Source: Lookfantastic Face Serum List (2022)

Secondly, as shown in Figure 1.10**,** customer reviews could be found on a product detail page, with a specific number of reviews with ratings at 5 scores, one tab “See all reviews” and another tab “Create a review”. Notably, the system only shows ten pieces of reviews without clicking “See all reviews” (*Lookfantastic Product Details*, 2022).



Figure 1.10 - Product reviews on the detail page

Source: Lookfantastic Product Details *(2022)*

The third place where reviews are presented is shown in Figure 1.11. Each piece of review consists of eight categories of data. Some can be classified as structured data or quantitative data, such as *Rating* and *Date*, while some others should be classified as unstructured data or narrative data, such as the *Title of review*, *Body of review,* and *name of reviewers*.

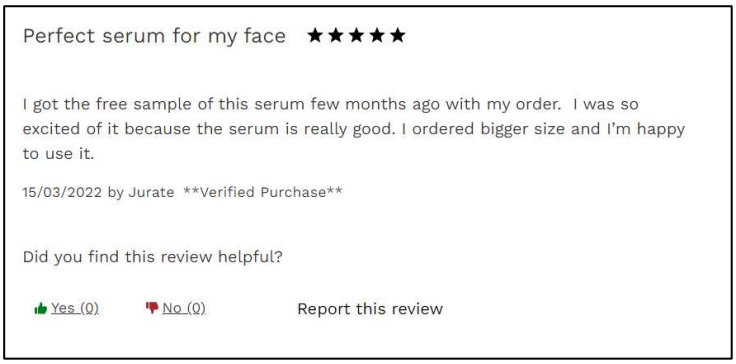


Figure 1.11 - Narrative reviews presented on product detail page

Source: Lookfantastic Product Details *(2022)*

Information in one piece of review could be summarized as:

- **Title of review:** Perfect serum for my face
- **Rating:** 5 stars
- **Body of review**: I got the free sample of …. And I'm happy to use it.
- **Date:** 15/03/2022
- **Name:** By Jurate
- **If verified purchase:** Verified purchase
- **If helpful:** 0 YES and 0 NO
- **Report this review**

A collection of three places in Figure 1.9, Figure 1.10, and Figure 1.11 contain a large volume of online review data, which might be easily neglected but once appropriately used could yield valuable customer experience insights.

The moment at which customers create a piece of review also matters. Customers may create a piece of review either before or after they buy a product from LOOKFANTASTIC®. In the former case, online reviews might reflect their expectation in the pre-core stage (Voorheesa et al., 2017), which, for example, could be effected by their previous experience. But the latter case is more common --- people tent to share their opinions in form of ratings and

short comments after they finish shopping (Voorheesa et al., 2017). These two conditions could be distinguished if the signal “Verified purchase” appears.

A form needs to be filled out to collect reviews from customers, as shown in Figure 1.12. There are five mandatory lines to be filled before creating a review otherwise the review cannot be submitted. This mechanism ensures the completeness of the information contained in one piece of review. Nevertheless, it also has some flaws. For example, it only provides a universal rating and a piece of general short comment and does not provide individual attributes ratings or text reviews labeled by several core attributes, such as on-time delivery, and product availability. Notably, *Gender* and *Age Range* are set to be optional fields out of respect for privacy.

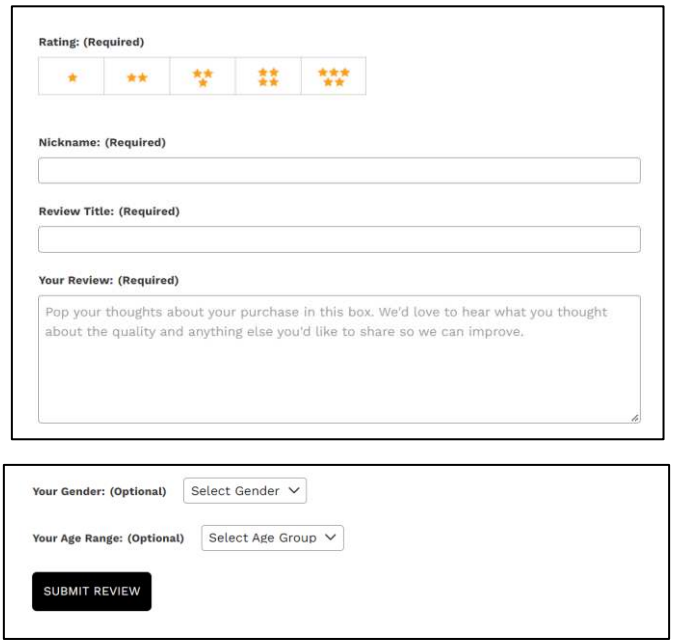


Figure 1.12 - A form to be filled to create a piece of review

Source: Lookfantastic Product Details *(2022)*

After submitting the review, the user will receive a notification on the top of the page like Figure 1.13 and the review will appear shortly after going through a moderation process.

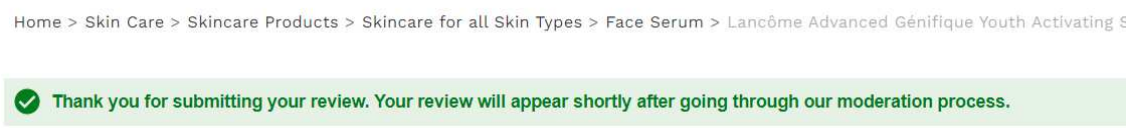


Figure 1.13 - A notification of submitting a review successfully

Source: Lookfantastic Product Details *(2022)*

1.3 Case Study Questions

After reviewing the background of LOOKFANTASTIC®, the basics of *Face Serums* plus corresponding ecommerce services during the purchasing journey, and the review system provided by LOOKFANTASTIC®, the two research questions formed in §1.1 are restated in Table 1.6 and specified with five research objectives. Notably, with the pedagogical purpose of training students in gaining customer experience insights with digital skills, these research objectives and questions were also designed to be approached and answered by the target audience.

Table 1.6 - Research questions and objectives

Research Questions	Research Objectives
1) What is the association between customer satisfaction and the price levels of *Face Serums*, based on all current product ratings of *Face Serums*?	1) To classify *Face Serums* into different levels.
	2) To analyze whether customer satisfaction is different among different levels of *Face Serums*.
	3) To analyze whether a certain association exists between customer satisfaction and levels of *Face Serums*.
2) Can customer sentiments towards *Face Serums* at different levels be extracted from all current textual reviews of *Face Serums*?	4) To determine general and emotion keywords and identify them.
	5) To identify the customer sentiments polarity for *Face Serums* at different levels.

2 Methodology

A pedagogical case study helps students by applying acquired theoretical knowledge to the real world. This type of work promotes the development of skills and students working through career-related issues could also gain applied experience.

This pedagogical case study of LOOKFANTASTIC® was developed to show students how ecommerce reviews could be leveraged to understand customer experience and how these insights contribute to specific business areas, and during this process, multiple data analysis techniques could be learned and applied in their future careers.

Specifically, this study was based on secondary data obtained from the website of LOOKFANTASTIC®. The time horizon was cross-sectional, as the secondary data collection occurred at two single points of time through a combination of web crawling[1] and manual methods. The case resolution will highly rely on a variety of data analysis methods. To provide the readers a preview, data analysis methods are summarized in Table 2.1 and will be further elaborated in §3.5.

Table 2.1 - A summary of research methods

Stages		Research Question 1			Research Question 2		
		Tasks	Software	Tool	Tasks	Software	Tools
1	Data collection & data storage	Web crawling name, price, rating and number of reviews	Python	Respects Beautiful Soup Pandas	Manually collect title, body, date and rating of all reviews	Excel	
2	Data processing	Remove unrelated products, duplicates, currency lables and split variables	Excel	Excel fuctions	6 text pre-processing tasks	Python	xlrd, nltk, re
3	Data analysis	Objective 1	Spss	"Frequency" and "Transform"	Objective 4	Python	Sentiment Analysis dictionary: AFINN-111
		Objective 2	Spss	ANOVA test or Kruskal-Wallis H test	Objective 5	Python	Sentiment Analysis library: Textblob
		Objective 3	Spss	ANOVA test or Ordinal Logistic Regression Analysis			

[1] A web crawler (also known as a robot or a spider) is a system for the bulk downloading of web pages. The basic web crawling algorithm is simple: Given a set of seed Uniform Resource Locators (URLs), a crawler downloads all the web pages addressed by the URLs, extracts the hyperlinks contained in the pages, and iteratively downloads the web pages addressed by these hyperlinks (Olston & Najork, 2010).

3 Pedagogical Notes

3.1 Target Audience

The target audience of this pedagogical case study is master students in business areas such as Marketing, particularly with interests in ecommerce. Students can have a better understanding of customer satisfaction and customer sentiments in a real-world situation, especially regarding the skincare products, *Face Serums*. Further, they will also know how to apply the knowledge about these components of customer experience in their future job. This case study also trains students in digital skills.

Additionally, theoretical and practical knowledge learned from this pedagogical case study might also be applicable at a business level, such as in Digital Marketing, Customer Relationship Management, and Product Development departments.

3.2 Learning Goals

According to Bloom's Taxonomy (Charlotte, 2021), master students, the target audience of this pedagogical case study, are expected to build foundational knowledge in lower-level introductory courses and then move step by step into the applying and analyzing stages. As noted in §1.3, research questions are designed to be the case questions answered by the master students by the end of the pedagogical case study. Thus, after the resolution of the case, master students are expected to achieve the following learning goals, which are fully compatible with case study answers to research questions:

- Define the customer experience and lists its five components
- Describe the customer satisfaction and customer sentiments
- Recognize the classic approaches to customer experience research.
- Recognize the two types of online review data and their applications in business.
- Recognize some simple text mining techniques in accessing textual data.
- Use web scrawling tools to obtain online review data.
- Use different methods to analyze numeric and narrative reviews.
- Interpret the results and generate customer insights.
- Relate insights about customer experience to specific initiatives in such as Online Marketing, Product Development, or Customer Relation Management

3.3 Literature Review

This Literature Review was developed according to Research Questions stated in §1.3.

Related works were reviewed to provide knowledge about customer experiences and their components. Classic approaches such as service quality and new methods based on online reviews were notably covered. The main findings were summarized in §3.3.3.

3.3.1 Customer Experience

This section will clarify the definition of customer experience and specifically introduce two well-developed dimensions of customer experience: customer perception and emotions. The main works are summarized in Table 3.1.

3.3.1.1 Customer Experience Conceptualization

Nowadays, customer experience is receiving much attention in the scientific and managerial community (Johnston & Kong, 2011; Trischler et al., 2018) and the phenomenon of customer experience is considered a new direction in the area of marketing (HAVÍŘ, 2017). Good customer experience management may improve customer satisfaction (Liljander & Strandvik, 1997), support the brand (Berry & Carbone, 2007), delivers customer loyalty (Mascarenhas et al., 2006), and also creates emotional bonds (Pullman & Gross, 2004) with customers, which might influence purchasing behaviours and financial performance.

There appears to be a good deal of confusion in the literature about the definition of customer experience (Johnston & Kong, 2011). One stream defines customer experience from the organization's point-of-view (Johnston & Kong, 2011) that it is a process, a journey, or a flow. For example, Lemon & Verhoef (2016) conceptualized customer experience as an iterative and dynamic process that flows from prepurchase to purchase to the postpurchase stage. Another main stream of literature (Csikszentmihalyi, 2000; Ding et al., 2010; Pullman & Gross, 2004) argued from the customers' perspective that it is, such as the personal interpretation (Johnston & Kong, 2011), internal or subjective response (Meyer & Andre, 2007) or assessment (Zomerdijk & A.Voss, 2010) to any direct contact or the indirect interactions through the company's offerings, such as the products, services, and brands (Meyer & Andre, 2007). In this sense, no two people can have the same experience. Major accepted definitions (Schmitt, 1999; Brakus et al., 2009; Keyser et al., 2015; McCarthy & Wright, 2004) expand the definition of customer experience by incorporating cognitive, emotional, behavioral, sensorial, and social components.

Overall, an integrated notion was developed in this work that customer experience is the customer's cognitive, emotional, behavioural, sensorial, and social responses to the firm or the firm's offerings during the purchase journey. This multidimensional construct plays a leading role in this work. In the following section, under the scope of customer experience, two well-developed components will be elaborated on.

3.3.1.2 Customer Perception and Emotion in Customers Experience Measurement

Customer experience measurement plays a critical role in making insights actionable, but as it is such a dynamic and multidisciplinary construct, no strong customer experience scales have been developed yet. (Lemon & Verhoef, 2016). Nevertheless, many efforts have been made to serve as the building blocks to the understanding of customer experience.

The most developed aspects of customer experience concern **customer perception** (Lemon & Verhoef, 2016), the "organization, identification, and interpretation of sensory information in order to represent and understand the presented information or environment" (Wikimedia, 2022). In psychology research, perception is one of the functions of cognition (Broscha et al., 2013), thus the cognitive component of overall customer experience could be partially grounded in customer perceptions.

Customer perception is primarily focused on two strong established concepts, perceived service quality (SQ) and customer satisfaction (CS). Service quality was measured by the multiple-item scale SERVQUAL (Parasuraman et al., 1988) and viewed as arithmetic differences between consumers' perceptions and expectations of the company's performance. Specifically, the 22 measurement items were categorized into five dimensions: Tangibles, Reliability, Responsiveness, Assurance, and Empathy. Customer satisfaction, on the other hand, is also influenced by both expectation and perception as well, according to the expectancy-disconfirmation model (EDM), a psychological mechanism introduced to the retail and service industry by Oliver's (1981). Customer satisfaction could be measured by, such as the "better than expected-worse than expected" scale (Oliver, 1980). When the actual performance of a specific product or service can't meet the customer's expectation, negative disconfirmation will occur and leads to customer dissatisfaction (Elkhani & Bakri, 2016).

Service quality (SQ) and customer satisfaction (CS) are distinct constructs. Parasuraman et al. (1988) emphasized that service expectations (E) represent predictions about what service providers "would" offer in the consumer satisfaction literature, but represent what they "should" offer or what is "essential" for excellent service in the service quality literature (Parasuraman et al., 1990). Oh (1999) posited that SERVQUAL measures the disconfirmation arithmetically

while the EDM model measures disconfirmation subjectively, especially when a "better than/ worse than" measurement is adapted (e.g. Bolton,1998). In addition, Parasuraman et al. (1988) stated that perceived service quality is the judgment based on an entity's overall excellence while customer satisfaction is more transaction-specific, whereas some other researchers (e.g. Dabholkar, 1993) embrace the notion that both SQ and CS can be examined meaningfully from both transaction-specific as well as global perspectives.

Though service quality (SQ) and customer satisfaction (CS) are not equivalent, there is a certain causal relationship between them. In fact, the direction of causality of SQ and CS has been widely debated by researchers (Parasuraman et al., 1994). For example, as Oliver (1981) said, "satisfaction soon decays into one's overall attitudes toward purchasing products" while a different opinion was held by Cronin (1992) that service quality leads to customer satisfaction, and not vice versa. Nevertheless, Parasuraman et al. (1994) enhance the knowledge of the interrelation between SQ and SQ by proposing both a transaction-specific conceptual model as well as a global framework -- the customer's assessment of service quality, product quality, and price determine their satisfaction towards a single transaction, and then an aggregation of transition-specific satisfaction leads to overall quality perception.

Classic approaches to measuring service quality and customer satisfaction have some limitations, one regards the validity of the survey (Oh, 1999). Extant literature has widely utilized SERVQUAL using survey-based questions, but as noted by Teas (1993), a considerable portion of the variance in the SERVQUAL expectations measures may be caused by respondents' misinterpretations of the question rather than by different attitudes or perceptions. Despite alternative approaches with higher validity being proposed for accessing customer experience, such as the Evaluated Performance (EP) Framework (Teas, 1993), this issue caused by the nature of survey-based methods has not been fundamentally solved. On the other hand, a multi-item scale like SERVQUAL provides a rather comprehensive measurement, but it is not simple enough in marketing practice and unable to capture customer experience in situ (Lemon & Verhoef, 2016).

Customers' emotion, which deepens the understanding of customer perception (HAVÍŘ, 2017), is another well-developed aspect of customer experience and its importance in overall customer experience measurement was recognized by many marketing researchers as well. Experiencing a service results in the customer feeling emotions, of which there are many hundreds and the main ones are happiness, surprise, love, fear, anger, shame, and sadness Johnston & Kong (2011). Early in the 1980s, experiential theorists (Holbrook & Hirschman, 1982; Hirschman & Holbrook, 1982) encouraged a broader view of human behaviour,

especially recognizing the importance of the emotional aspects of experience. Du et al. (2011) stated that researchers should put forward the importance of studying customers' emotions to avoid service failure in the post-core stage of purchasing journey.

The measurement of emotion has been involved in many conceptual models as well, such as the Consumption Experience Model (Fornerino et al., 2006), Customer Experience Model (Gentile et al., 2007), and EXQ framework (Klaus & Maklan, 2012), all of which were built upon the perception of the consumer as a human being with emotions. However, these conceptual models are also designed to be survey-based and respondents can only express their feelings based on given questions, for example, respondents are asked to rate the degree of agreement towards "I am confident in their expertise" in the "Peace of mind" in EXQ framework.

Additionally, more models for accessing online retail services have been proposed with the rising of ecommerce. For example, Szymanski & Hise (2000) initially suggested that convenience, site design, and financial security are the dominant factors in consumer assessments of e-satisfaction, and similar factors were proposed by the eTailQ model (Wolfinbarger & Gilly, 2003) and E-S-QUAL Model (Parasuraman et al (2005). Posselt & Gerstner (2005) specifically found that the impact of post-sale factors on overall satisfaction rating is much stronger than the impact of pre-sale factors and the post-sale factors have an impact on the following order: (1) on-time delivery; (2) product met expectations; (3) customer support; and (4) availability. Moreover, You et al. (2016) listed 15 ecommerce service attributes and further compared their importance rank in different categories.

Notably, traditional data methods such as online surveys, questionnaires, and interviews have been widely applied by survey-based research projects on customer experience (HAVÍŘ, 2017). These methods have been criticized to be costly, labor-intensive, time-consuming, or ignoring the co-creation role of customers (Trischler et al., 2018) who are "experts of their experience" (Sanders & Jan Stappers, 2016). In this respect, there is a need to develop an efficient way to insight into customers (Wang, W & Tian, Z, 2019) and as suggested by Chatterjee et al. (2020), user-generated content should be used to access the customer outcomes, and online review has been recognized as such type of data (Park, 2019).

To conclude, this section reviewed classic conceptual models concerning customer perception and emotion and the critical works were summarized in Table 3.1 below. In respect of accessing customer perception, service quality and customer satisfaction play an important role but they are recognized as two distinct but relevant constructs. The measure of customer emotion was captured in many conceptual models as well, notably, some others expand to

ecommerce. However, classic approaches have some limitations. Firstly, classic scales are not simple enough and unable to measure customer experience in situ. Secondly, survey-based studies might lead to respondents' confusion, and given survey questions might yield a limited understanding. Additionally, traditional data collection methods used in the survey are labor-intensive and time-consuming. Overall, there is a need to resort to a more effective way of accessing ecommerce customer perception and emotion by leveraging "user-generated data".

Table 3.1 - A summary of classic approaches

Model	SERVQUAL	Expectancy-Disconfirmation model EDM	Consumption experience model	Customer experience model	EXQ framework	E-S-QUAL Model	eTailQ	post-sale e-satisfaction factors	ecommerce service attributes
Dimensions	Tangible	sampling benefits	Perceptual	Sensorial	product experience	efficiency	web design	on-time delivery	15 factors: product met expectations, customer support, on-time delivery, satisfaction with check out, variety of shopping options, shipping charges, return process, ease of finding what you are looking for, product availability, design of site, product selection, order tracking, price relative to other online retailers, charges stated clearly, clarity of product information
	Reliability	problems	Affective	Emotional	outcome focus	fulfilment	fulfilment	product met expectations	
	Responsiveness	overall satisfaction	Physical	Cognitive	moment of truth	system availability	security	customer support	
	Assurance		Social	Pragmatic	peace of mind	privacy	customer service	availability	
	Empathy		Cognitive	Lifestyle					
				Relational					
Note	measure service quality	measure satisfaction	emotion included	emotion included	emotion included	ecommerce	ecommerce	ecommerce	ecommerce; ranked in different product categories
Reference	(Parasuraman et al., 1988)	(Oliver, 1981)	(Fornerino et al., 2006)	(Gentile et al., 2007)	(Klaus & Maklan, 2012)	(Parasuraman et al (2005)	(Wolfinbarger & Gilly, 2003)	(Posselt & Gerstner, 2005)	(You et al. 2016)

3.3.2 Online Review

This section provided an overview of online reviews and specified the applications of two main types of online reviews respectively in accessing ecommerce customer satisfaction and customer emotion. The main works are summarized in Table 3.2 and Table 3.3.

3.3.2.1 Overview

The 2000s have seen the explosive growth of online reviews (Stine, 2019) and the enormous number of user-contributed content on the Internet is extremely rich in information on all aspects of everyday life of a great number of people, such as their opinions, their experience, their observations, about the products and services they buy and use or the events around them

(Gelbukh, 2017). Online feedback is a combination of unprecedented scale, being controllable by information system designers, the absence of contextual cues (Chrysanthos, 2009), and is public and common to all customers as well as sellers (Kwark et al., 2014).

The chaotic and noisy streams of data contained in online reviews, once put to good use, may benefit both **consumers,** when it comes to their decision-making (Basani et al., 2019; Sivakumar & Uyyala 2021; Cataltas et al., 2020; Rohman et al., 2020; Liu et al., 2020; Rahul et al., 2019; Singla et al., 2017) and **sellers** (Gelbukh, 2017) by providing valuable customer insights that their actions should be based on, such as in product design (Ireland & Liu, 2018; Ng et al., 2021; Cataltas et al., 2020; Jin et al., 2016), product improvement (Rohman et al., 2020), product development strategies (Ezhilarasan et al., 2019; Alasmari, 2020), ecommerce product quality management (Liu et al., 2020), customer relationship management (Ezhilarasan et al., 2019), management strategies (Hadju & Jayadi, 2021), marketing strategies (Rahul et al., 2019; Alasmari, 2020).

Studies on online reviews cover a wide range of sectors, such as Fast-Moving Consumer Goods (FMCG), Healthcare, Consumer Electronics, Service Sector, Fashion, Entertainment Industry, etc, as shown in Table 3.2.

Table 3.2 - A summary of studies on online reviews by different sectors

Industry	Categories	Literature
FMGP	Lipstick	(Kun Indarta & Romadhony, 2021)
	Beauty Product	(Mahfiz & Romadhony, 2020) (Y. Xiao et al., 2021) (Danendra & Sibaroni, 2021)
	Hair care product	(Kothalawala & Thelijjagoda, 2020)
	Baby products	(Y. Xiao et al., 2021)
	Groceries	(Hadju & Jayadi, 2021)
	Commodity	(Shah et al., 2021)
	Consumer products	(Stephenie et al., 2020)
Healthcare	Healthcare and subgroups	(Chatterjee et al., 2020)
Fashion	Fashion	(Hadju & Jayadi, 2021)
	Clothing	(Yu & Bai, 2021)
Consumer Electronics	Mobile phone	(Sivakumar & Uyyala, 2021) (Pathuri & Anbazhagan, 2020) (Meenakshi et al., 2020) (Dadhich & Thankachan, 2022) (F. Wu et al., 2020)
	Digital products	(H. Wang et al., 2020) (Jagdale et al., 2019)
Service sector	Hotel	(Khotimah & Sarno, 2019) (Chiny et al., 2021)
	Airline	(Siering et al., 2018)
	Restaurant	(Nithin & Poornalatha, 2018) (Chugh et al., 2020)

	Fast food restaurant – KFC	(Ramdhani et al., 2018)
Entertainment	Movie	(Xu et al., 2020)

Relevant works of literature have studied online reviews presented by different review systems as shown in Table 3.3. This thesis categorized the platform where reviews are provided as ecommerce, social media, third-party review websites, or other types.

Table 3.3 - A summary of review systems on different platforms

Types	Examples	Review System	Literature
Ecommerce	Amazon	Universal rating system -from 1 to 5 stars; Short comment; Image review	(Rao & Sindhu, 2021) (Jiang et al., 2021) (Dadhich & Thankachan, 2022) (Shah et al., 2021) (Xu et al., 2020) (Cataltas et al., 2020)
	Alibaba	Universal rating system -from 1 to 5 stars; Short comment	(W. Zhao, 2020)
	eBay	Positive, negative, or neutral rating plus short comment; Ratee may post a response	(Ba & Pavlou, 2002) (Lucking-Reiley et al., 2007)
	Marketplace.com		(Rohman et al., 2020)
	Jingdong Mall	Universal rating system -from 1 to 5; Short comment labeled by individual attributes; Image review	(S. Xiao et al., 2020) (H. Wang et al., 2020) (Wu et al., 2020)
	Flipkart	Universal rating system -from 1 to 5 stars; Short comment; Image review	(Dadhich & Thankachan, 2022) (Shah et al., 2021)
	Tokopedia.com	Universal rating system -from 1 to 5; Short comment labeled by individual attributes; Image review	(Stephenie et al., 2020)
Social media	Microblog	Short comment; Image review	(Shobana & Murali, 2020) (Subbaraju et al., 2020) (Lakshmidevi et al., 2019)
	Twitter	Short comment; Image review	(Anjan Babu et al., 2017) (Ng et al., 2021) (Ramdhani et al., 2018) (Kumari et al., 2018)
	YouTube	Short comment;	(Ramdhani et al., 2018)
Review-website	airlinequality.com	Short comment; Universal score from 1 to 10 and seven individual attribute ratings;	(Siering et al., 2017)

	Trustpilot.com	Universal rating system -from 1 to 5 stars; Short comment	(Chatterjee et al., 2020)
	Female Daily	Universal rating system -from 1 to 5 stars; Short comment	(Arthamevia et al., 2021)
Others	Airbnb	6 basic indicators on a scale of 10 and an overall score	(Chiny et al., 2021)

It can be observed from Table 3.3 that numeric ratings and short comments are the most common formats of online review presented by a majority of review systems. It was suggested that both qualitative and quantitative review data should be combined (Chatterjee et al., 2020) to maximize the value of this user-generated content. The combination of numerical rating and textual content could be seen in many works (C. Zhao, 2020; Pathuri & Anbazhagan, 2020; X. Wang et al., 2022; Chadchankar et al., 2020; Singh & Sarraf, 2020; Brownfield & Zhou, 2020; F. Wu et al., 2020; Srikanth et al., 2021; So, 2020). Both types of reviews, in aggregate, represent a wealth of information on understanding customer experience and contain critical intelligence for a wider range of domains.

To summarize, the online review, noted as "user-generated" content, has served to provide customer insights for different domains (e.g., product development, and marketing strategies) and received increasing attention from industries. The numeric review/online rating and the textual review/short comments are two main types of review data and play different roles in providing customer experience insights and these will be respectively covered in §3.3.2.2 and §3.3.2.3.

3.3.2.2 Evaluating Ecommerce Satisfaction Using Online Product Rating

As reviewed in the previous section, the online rating has been widely used in ecommerce when it comes to accessing historical customer satisfaction online (Peng et al., 2019; You et al., 2016; Pappas et al., 2014), which might affect the purchasing decision of potential consumers and go on to affect the organizations' bottom line (Chevalier & Mayzlin, 2006; Duan, Wenjing, Bin Gu, 2008).

A better understanding of online rating as a satisfaction indicator should be based on antecedents reviewed in §3.3.1. From the multidimensional view of customer experience conceptualized, online rating (Chatterjee et al., 2020) reflects customer perception and could be their responses to the firm or the firm's offerings during the whole purchasing journey. According to the expectancy-disconfirmation model (Oliver, 1981), the online rating is the

subjective disconfirmation between customer expectation and perception, and for a single transaction, it should be the joint assessment of service quality, product quality, and price (Parasuraman et al.,1994). In the context of ecommerce, customer ratings could be linked with a specific transaction and represent the overall satisfaction towards attributes including on-time delivery, customer service, web design, order tracking, etc. (Wolfinbarger & Gilly, 2003; Parasuraman et al., 2005; Posselt & Gerstner, 2005; You et al., 2016).

Early literature has tried to link online customer rating with **sales and price fluctuation**, where the decision-making of potential customers always serves as the intermediary, although the findings have been very mixed. For example, some studies have shown that online rating is positively associated with sales growth (Clemons et al., 2006; Chevalier & Mayzlin, 2006; Dellarocas, 2003), whereas others found it hard to discern a strong correlation between customer ratings and outstanding (Li & Hitt, 2008). Researchers have also focused on pricing strategies for organizations. One stream of the literature suggested that better ratings induce higher trust which in turn leads to a higher price premium in the auction (Ba & Pavlou, 2002; Houser & Wooders, 2006; Kalyanam & McIntyre, 2001) and this relationship was specifically found to be stronger for expensive products as there is greater risk inherent in the exchange products (Ba & Pavlou, 2002). Another research stream holds different opinions that there is no effect from positive feedback while negative feedback may reduce the price (Lucking-Reiley et al., 2007); Furthermore, some scholars even suggest that both forms of feedback do not affect price contingent on sale (Resnick et al., 2006). In addition to the focus on sales and price, the intermediate role of online reviews has also been studied as they are public and common to all customers. For example, Hu et al. (2006) stated that only when some conditions are met can mean ratings serve as a valid representation of the product's quality and that is when all the consumers write a product review or there is a symmetric impact of bragging and moaning for consumers leaving a review.

Evaluating customer satisfaction using online customer ratings is different from classical approaches that accessing customer perception, one of the most influential is service quality measured by the SERVQUAL scale (Parasuraman et al. 1988). First of all, the online rating is an indicator of customer satisfaction (Chatterje et al.,2020) and it measures disconfirmation subjectively whereas the service quality measures the disconfirmation arithmetically (Oh, 1999). Secondly, the online rating is much lighter, more accessible, and easier to be understood by either managers or customers while service quality is measured by a more complicated scale. Thirdly, the measurement of service quality was initially designed to be survey-based that information was gathered using traditional methods such as questionnaires, and interviews.

While online rating was born to be "user-generated" content free of biases resulting from a survey and also eliminate the labor-intensive, and time-consuming limitations in collecting customer experience data. Lastly, online ratings, especially ecommerce customer reviews, provide first-hand information about every single transaction (*e.g.* You et al., 2016) while service quality provides more global measurement.

Overall, as a "user-generated" customer satisfaction metric, online rating differs from the measure of service quality in many aspects. Features that make online reviews superior to the classical approach in accessing customer perception include: being more accessible, understandable, transaction-specific, and of large volume.

3.3.2.3 Detecting Customer Sentiment Using Online Textual Reviews

Textual reviews, wherein a customer can pour his/her heart out either in frustration or happiness are certainly one of the best in terms of 'informative content' (Chatterjee et al., 2020). As another main type of online review, it is more powerful than online rating and also moves beyond the traditional approaches to accessing customer sentiment.

Extant literature has covered similar dimensions of the importance of text reviews to those of numeric ratings, as both of them are parts of online reviews. For organizations, the positive impact of favourable textual review goes to price, sales, and profits (e.g. Ajorlou et al., 2018). For customers, online reviews may influence many aspects of their purchase decision-making process (e.g. Dorner et al., 2013). For example, text reviews of the product may help the customers to understand product quality (Dey et al., 2020). Nevertheless, textual reviews are different from numeric reviews in nature. Textual review is a type of "unstructured data" presented in natural human language and usually needs to be processed by a combination of text mining and text analysis techniques (Chatterjee et al., 2020). Whereas numeric rating is more comprehensible and useful as a type of "structure data" and it can be accessed with typical qualitative analysis methods, such as the Mean Value and ANOVA (Juanatas et al., 2019).

Despite abundant applications of leveraging online reviews in generating customer experience insights, this study particularly focuses on sentiment analysis as it is the top research field of text analysis (Jagdale et al., 2019) and noted as the most common text analytics method (Chatterjee et al., 2020). Sentiment analysis is a process of computing and categorizing the expressed opinions of people about a certain event, subject, or product as positive, negative, or neutral (Thangavel & Lourduswamy, 2021). Based on an online review, the main task of sentiment analysis is to identify what feelings or emotions (Gelbukh, 2017) the textual reviews may express.

In assessing customer sentiment or emotion, sentiment analysis outperforms traditional survey-based conceptual models, such as the Consumption experience model (Fornerino et al., 2006), Customer experience model (Gentile et al., 2007), and EXQ framework (Klaus & Maklan, 2012), as it could benefit from a large volume of textual reviews generated by customers online; More importantly, as sentiments analysis is the use of a group of computing techniques to understand customers emotion from the text (Thangavel & Lourduswamy, 2021), it outdo traditional approaches where narrative information collected from respondents were read and processed manually.

As a relatively new topic in marketing research, some basics of sentiment analysis need to be clarified. First of all, sentiment analysis may be conducted at different levels. It can be done at a whole document level or sentence level, that is to identify the reviewers' sentiment toward a specific entity, e.g., airline (Siering et al., 2017). Another form of sentiment analysis is aspect-based, which is to tease out the customer sentiment regarding specific aspects, such as the product aspects (e.g. Appearance, smell, taste, and mouthfeel of beer) (Peng et al., 2019). Thus, aspect-based sentiment analysis requires additional efforts in determining the aspects.

Secondly, sentiment analysis can be conducted using different approaches. The dictionary-based approach (Chatterjee et al., 2020) counts the words in the text based on a dictionary of emotional terms (Stine, 2019), and the Machine learning approach automatically classifies the sentences, documents, or aspects into ones with positive or negative sentiments according to rules predefined by a human. More details of these approaches have already been widely discussed in studies in the field of IT, but those are beyond the scope of this thesis. The dictionary-based approach is the earliest form of sentiment analysis and remains popular because of its simplicity and ease of use. For example, the AFINN lexicon[2] assigns a numerical sentiment score from −5 to +5 to types of words; The NRC lexicon[3] includes 8 basic emotions such as "anger" and "joy" (Chatterjee et al., 2020). In addition, Harvard General Inquirer Lexicon[4] and Textblob Lexicon[5] have also been widely used, such as by Siering et al. (2018) and Xiao et al. (2021).

To conclude, the textual review is more informatic than online ratings and has many advantages over the traditional survey-based conceptual models in terms of accessing customer

[2] The AFINN lexicon is a list of English words rated with an integer between -5 (negative) and +5 (positive).
[3] The NRC Emotion Lexicon is a list of English words associated with eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and two sentiments (negative and positive).
[4] The Harvard General Inquirer is a lexicon for analysing textual data developed in 1960s.
[5] TextBlob is a library for processing textual data and help to calculate the sentence's sentiment polarity.

emotions. Especially, sentiment analysis is the computing technique to be used to detect customer sentiment from textual reviews.

3.3.3 Summary of Literature Review

Guided by the two case study questions in §1.3, this Literature Review reviewed the theoretical foundation, classic approaches, and new approaches for accessing customers' perceptions and emotions in ecommerce.

As reviewed in §3.3.1, customers' perception, referred to as "interpretation of sensory information", and customers' emotions, including "happiness, surprise, love, fear, anger, shame, and sadness", are two important components of the multidimensional construct of customer experience. As summarized in Table 3.1, customer perception has been initially covered in the measure of service quality and customer satisfaction, and the measure of customers' emotions has been covered in conceptual models such as EXQ framework (Klaus & Maklan, 2012). Moreover, the scenario of measuring customer experience was expanded to ecommerce service as well. However, classic constructs are too complicated, and survey-based measurements of customers' perception and emotions might result in biases in customer insights and limit the breadth of understanding. Additionally, traditional information collection methods being used in the survey are labour-intensive and time-consuming. In the digital age, user-generated content has been proved to provide better solutions for gaining customer experience insights and online customer review has received much attention in this field.

§ 3.3.2 showed that numeric ratings and textual review are two main formats of online review. In ecommerce, customer rating is widely used as an indicator of ecommerce customer satisfaction. Compared with classic approaches to accessing customer perception, it is simpler, accessible, understandable, transaction-specific, and of large volume. Textual review is more informative that customers' emotions and sentiments have already been extracted from short comments, and this process relies on sentiment analysis techniques. The combined use of numeric ratings and textual reviews maximized the value of this user-generated data in customer experience research.

3.4 Case study lecture plan

A set of learning goals designed for master's students was presented in §3.2. To train students to gain customer experience insights based on online reviews, this advanced training programme will follow the animation plan in

Table 3.4, which was designed in accordance with the nine learning goals proposed in §3.2.

Table 3.4 - Animation plan

No.	Learning Goals	Materials	Format of Activities	Time
1	Define the customer experience and lists its five components	Lecture	contact lessons	1 lesson (45 min)
2	Describe the customer satisfaction and customer sentiments	Lecture	contact lessons	1 lesson (45 min)
3	Recognize the typical research approaches to customer experience.	Lecture	contact lessons	1 lesson (45 min)
4	Recognize the two types of online review data and their applications in business.	Lecture	contact lessons	1 lesson (45 min)
5	Recognize some simple text mining techniques in accessing textual data.	Lecture	contact lessons	1 lesson (45 min)
6	Use web scrawling tools to obtain online review data.	Tutorial Python	contact lessons; off-class group preparation	1 lesson (45 min) 3h off-class
7	Use different methods to analyse numeric and narrative reviews.	Tutorial SPSS, Python	contact lessons; off-class group preparation	1 lesson (45 min) 3h off-class
8	Interpret the results and generate customer insights.	-	contact lessons: group presentation	1 lesson (45 min)
9	Relate insights about customer experience to specific initiatives	-	contact lessons: group presentation	1 lesson (45 min)

3.5 Case Resolution

The case resolution progressed in two stages following two research questions and research objectives defined in §1.3, and the case resolutions in §3.5.3 and §3.5.4 were implemented by following the guidance from §3.5.1 and §3.5.2.

3.5.1 Research Methods for Q1

Q1: *What is the association between customer satisfaction and the price levels of Face Serums, based on all current product ratings of Face Serums?*

3.5.1.1 Data Collection and Storage

Data was crawled using Python.

According to the first research question, *name, price, ratings, and the number of reviews*, as shown in Figure 1.9 and Figure 1.10, were crawled from the LOOKFANTASTIC® International site (*Lookfantastic International*, 2022) using web scrapping tools ***Respects, Beautiful Soup,*** and ***Pandas,*** which are developed on ***Python.*** The web crawler was written in Python 3.6[6] and was presented in Appendix 4 – Programming with Python – Part 1. The data being crawled by web scraping techniques were automatically saved into Excel sheets for further manipulation.

3.5.1.2 Data Processing

This stage was completed in Excel.

Firstly, duplicated products or products that should not be categorized as *Face Serums,* such as *Cream* or *Face cleansers,* were eliminated from the file.

Secondly, the brand and the volume of each product were collected from its full name. For example*,* "The INKEY List Beta Hydroxy Acid Exfoliant 30ml" is the full name of a product*,* which contains the brand "The INKEY" and the volume "30ml". Then, *brand* and *volume* were obtained from this name were saved as two individual variables. Dividing the price of 11.45 € by its volume of 30ml led to another variable, *price per 30ml*, which made the price of all *Face Serums* more comparable.

Thirdly, after formatting the data, such as removing the currency signal or identifying the missing value, seven categories of data remained in Excel, *brand, name, volume, price per 30ml, actual price, rating, and the number of reviews* were cleaned and passed into SPSS.

3.5.1.3 Data Analysis

SPSS 27 was adopted to achieve Research Objectives 1, 2, and 3 in accordance with Research Question 1, as stated in §1.3.

Research Objective 1 *is to classify Face Serums into different levels*. Indeed, there have been market class levels for certain categories of products or services, such as *Market class levels for the hotel* (e.g., luxury, upper scale, upscale, upper midscale, midscale, economy) or *Beer Karma (BK) points* to classify beer lovers as beginners (BK< 100), beer lovers (100 ⩽ BK<500), and experts (BK⩾ 500) (Peng et al., 2019). However, a well-developed market class

[6] Python is a computer programming language often used to build websites and software, automate tasks, and conduct data analysis. For more details, please check the link: https://www.coursera.org/articles/what-is-python-used-for-a-beginners-guide-to-using-python.

level for *Face Serums* has not been developed yet. So, this section classified *Face Serums* into 10 levels by cutting the products into equal range of percentiles (10%, 20%, 30%...) based on their price.

Research Objective 2 *is to analyze whether customer satisfaction is different among these levels.* If product ratings are normally distributed among different levels of *Face Serums*, the Compare Means and ANOVA test could be used to explain the significance of the difference in product ratings among levels. But if product ratings do not follow a normal distribution, the non-parametric tests, Kruskal-Wallis H test[7] (Leard Statistics, 2022; Zehrer et al., 2011), would be more appropriate to be used. The decision will be made in §3.5.3. Four assumptions (Laerd Statistics, 2022b) checking the usability of the Kruskal-Wallis H test are:

- *A1-1: The independent variable should consist of two or more categorical, independent groups.*
- *A1-2: The dependent variable should be measured at the ordinal or continuous level (i.e., interval or ratio)*
- *A1-3: There is independence between observations, which means that there is no relationship between the observations in each group or between the groups themselves.*
- *A1-4: The distributions in all groups should have different shapes. Having similar distributions simply allows you to use medians to represent a shift in location between the groups, otherwise, you should use the mean rank[8].*

Research Objective 3 *is to analyze whether a certain association exists between customer satisfaction and levels of Face Serums.* Nevertheless, whether or not to measure this association depends on the results of Research Objective 2. When the continuous variable *rating* follows the normal distribution, ANOVA test could be used to measure the linear correlation. Otherwise, Ordinal Logistic Regression[9] would be adopted to analyze the association between the ordinal dependent variable level of Face Serums and the continuous independent variables rating. The decision will be made in §3.5.3. Similarly, four assumptions need to be checked (Laerd Statistics, 2022c):

[7] The Kruskal-Wallis H test is considered the alternative to the one-way ANOVA. It is *a rank-based* nonparametric test that can be used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable. For example, you could use a Kruskal-Wallis H test to understand whether exam performance, measured on a continuous scale from 0-100, differed based on test anxiety levels (i.e., your dependent variable would be "exam performance" and your independent variable would be "test anxiety level", which has three independent groups: students with "low", "medium" and "high" test anxiety levels). (Laerd Statistics, 2022b).

[8] The mean rank is the average of the ranks for all observations within each sample.

[9] For continuous independent variables (e.g., "age", measured in years), you will be able to interpret how a single unit increase or decrease in that variable (e.g., a one-year increase or decrease in age), was associated with the odds of your dependent variable having a higher or lower value (e.g., a one-year increase in participants' age increasing the odds that they would consider tax to be too high).

- *A2-1: The dependent variable should be measured at the ordinal level.*
- *A2-2: One or more independent variables that are continuous, ordinal or categorical.*
- *A2-3: No multicollinearity[10] when you have two or more independent variables.*
- *A2-4: Pass proportional odds assumption or parallel regression assumption [11].*

3.5.2 Research Methods for Q2

Q2: *Can customer sentiments towards Face Serums at different levels be extracted from all current textual reviews of Face Serums?*

3.5.2.1 Data Collection and Storage

All textual reviews of *Face Serums* were manually collected from all of their product detail pages (e.g., *Lookfantastic Product Details*, 2022). A full dataset will be provided on demand.

Four categories of review data were specifically considered, including *Title of reviews, Ratings, Body of reviews,* and *Date* as that presented in Figure 1.11. All these categories of data were stored in an Excel file, after which details about each *Face Serum* obtained in § 3.5.1.1, specifically the *brand, name, and price per 30ml*, were assigned to each piece of review.

Finally, a database was set up, covering multiple 7 categories of data: *brand, name, price per 30ml*, *Title of reviews, Ratings, Body of reviews,* and *Date*.

3.5.2.2 Data Processing

Python was used at this stage with code written in Appendix 4 – Part 2.

Body of reviews, an example of which is provided in Figure 1.11, is considered the main type of narrative data to be analyzed by this thesis, as *Body of reviews* are longer and contains more valuable information than other narrative parts, such as the *Title of reviews.*

The processing of *Body of reviews* used NLTK library[12] and followed a basic text pre-processing routine which contains 6 steps, with explanations being provided as followings:

- ***Eliminate spacing & unify letters to lowercase****: avoid duplicate words, such as "Product" and "product".*
- ***Tokenization:*** *split the textual reviews into parts so that the computer can recognize the words*

[10] Multicollinearity means that several independent variables in a model are correlated.

[11] Eacn independent variable has an identical effect at each cumulative split of the ordinal dependent variable.

[12] NLTK is a leading platform for building Python programs to work with human language data. It has been called "a wonderful tool for teaching, and working in, computational linguistics using Python," and "an amazing library to play with natural language." (The NLTK Team, 2022)

- ***Eliminate the non-alpha****: e.g., punctuations, as they are meaningless*
- ***Eliminate stopwords****: e.g., 'the', 'of', 'will', as they are meaningless*
- ***POS-tags****: To post a tag to each word depending on whether it's a noun or verb, etc.*
- ***Lemmatization:*** *Reverse the words into their original pattern based on the tags, such as reverse a noun "product" to "product" and reverse a verb "found" to "find".*

3.5.2.3 Data Analysis

Python was adopted to achieve Research Objectives 4 and 5 in accordance with Research Question 2, as stated in §1.3.

Research Objective 4 is *to determine general and emotional keywords and identify them.* The code used to extract keywords from textual reviews was written in Appendix 4 - Part 2. Notably, the dictionary *AFINN- 111***,** which was reviewed in § 3.3.2.3, was used to identify the emotional keywords, as it has the advantage of assigning a numerical sentiment score from −5 to +5 to words rather than a "positive" or "negative" label (Stine, 2019).

Research Objective 5 *is to identify the customer sentiments polarity for Face Serums at different levels.* The code used to calculate sentiment polarity was written in Appendix 4 – Part 3. Notably, lexicon *Textblob*[13] (Y. Xiao et al., 2021), which was reviewed in § 3.3.2.3, was used to calculate the *sentiment polarity score* of text reviews, after which several polarity scores ranging from -1 to 1 were to be presented. The logic is to count the positive and negative words and calculate the score using Polarity = (positive-negative) / (positive + negative). This process will be automatically achieved by a computer. One example is the study by Siering et al. (2018).

Overall, this section was mainly based on Dictionary-based Sentiment Analysis, which is the earliest form of sentiment analysis and remains popular because of its simplicity and ease of use (Stine, 2019). But more knowledge about sentiment analysis was reviewed in §3.3.2.3.

3.5.3 Answering Research Question 1

Again, guidance from §3.5.1 was followed to answer Research Question 1 stated in §1.3: *What is the association between customer satisfaction and the price levels of Face Serums, based on all current product ratings of Face Serums?* In this attempt, Research Objective 1,2, and 3 was achieved.

As shown in Table 3.5, 1147 *Face Serums* were obtained, along with their *name, actual retail price, rating,* and the *number of reviews*. 588 *Face Serums* were finally retained in the

[13] TextBlob is a Python library that help to calculate the sentence's sentiment polarity.

dataset, 361 of which have been reviewed in form of both ratings and textual reviews. A complete dataset containing 7 categories was provided in Appendix 1, including *brand, name, volume, price per 30ml, actual price, rating, and the number of reviews*.

Table 3.5 - Data collection results for Question 1

Categories	Counts
Total obtained	1147
Total remained	588
Have ratings and no reviews	361

(1) Objective 1

Research Objective 1 *is to classify Face Serums into different levels*.

Following the methods in §3.5.1.3, 588 Face Serums were classified into ten levels and each level represents 10% of products. The results of the descriptive analysis were provided in Table 3.6 and one could find that nearly half of *Face Serums* (from Level 1 to Level 5, 50%) are sold for less than 50.95 euros and only very few *Face Serums* (56, 10%) fall in the range from 124.5 euros to the upper bound 429.45 euros. Taking a closer look, the most representative brands from the cheapest Level 1 are *The Ordinary* and *Revolution* as these two brands respectively have the greatest number of products that fall into this level. So forth, representatives from the most expensive Level 10 are Chantecaille, RéVive,111SKIN, Dermalogica, Darphin, and La Mer.

Table 3.6 - Descriptive analysis

Level	Percentiles	Minimum	Maximum	Representative Brands
1	0-10%	3.45	11.45	The Ordinary, Revolution
2	10%-20%	12.27	20.96	The Ordinary, Clinique, BeautyPro
3	20%-30%	21.45	32.95	Pixi, Vichy
4	30%-40%	33.27	41.95	Antipodes, Eucerin, Medik8
5	40%-50%	42.95	50.95	Ecooking, Medik8
6	50%-60%	50.97	62.45	DECLÉOR, AHAVA
7	60%-70%	62.95	75.45	Lancôme, Filorga, Dermalogica
8	70%-80%	76.45	94.95	ALGENIST, Dr Dennis, Elizabeth Arden, Gatineau, Murad
9	80%-90%	95.34	124.45	Avant, Estée Lauder, Perricone MD
10	90%-100%	124.9	429.45	Chantecaille, RéVive,111SKIN, Dermalogica, Darphin, La Mer

By achieving Objective 1, 588 Face Serums are grouped into ten levels. From the cheapest level to the premium level, each level has its price range and the most representative brands.

(2) Objective 2

Research Objective 2 is *to analyse whether customer satisfaction is different among different levels of Face Serums.*

Figure 3.1 shows the *rating* of *Face Serums* does not follow a normal distribution. According to the guidance from §3.5.1.3, it is more appropriate to use the Kruskal-Wallis H test[14] to examine whether customer ratings are different among ten different levels, and data has passed four assumptions.

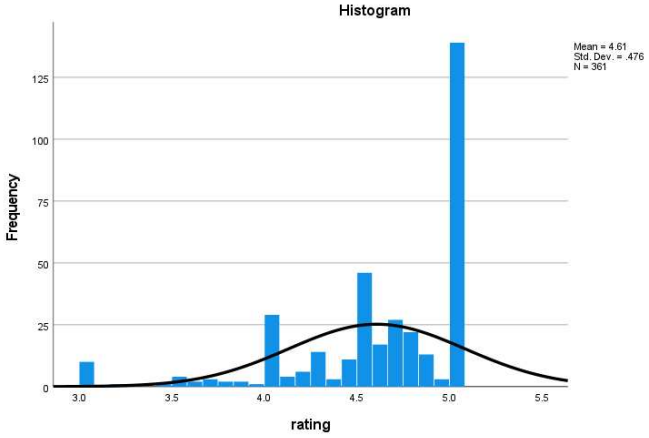


Figure 3.1 - Distribution of average ratings

First, the *level* is an ordinal independent variable consisting of 10 categories (A1-1). Secondly, the *rating* is the dependent variable measured by a continuous scale ranging from 0 to 5 (A1-2). Thirdly, *level* and *rating* are mutually independent (A1-3). Lastly, as shown in Table 3.7, sig = 0.008 < 0.05, indicating that the distribution of rating in all levels of *Face Serums* does not have the same shape and one can only use the Kruskal-Wallis H test to compare mean ranks (A1-3). Full results were provided in Appendix 2.

Table 3.7 - Hypothesis Test for Kruskal-Wallis

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of rating is the same across categories of group_level_588.	Independent-Samples Kruskal-Wallis Test	.008	Reject the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

[14] The Kruskal-Wallis H-test is a nonparametric test based on rank order and is used to test for differences in continuous or ordered categorical variables between multiple groups (which can also be two groups). (Meng Te Yi Shu Tong, 2022)

After checking the assumptions, the results of the Kruskal-Wallis H test in Table 3.8 showed that there was a statistically significant difference in *rating* among ten levels, $\chi 2(2) = 22.333$, $p = 0.008$, with a mean rank *rating* of 139.40 for Level 1, 162.78 for Level 2, 218.85 for Level 3, 224.85 for Level 10, and so forth.

Table 3.8 - Kruskal-Wallis H test

Ranks

	group_level_588	N	Mean Rank
rating	Level 1	50	139.40
	Level 2	37	162.78
	Level 3	40	165.29
	Level 4	35	197.50
	Level 5	38	183.87
	Level 6	34	199.07
	Level 7	36	218.85
	Level 8	31	175.00
	Level 9	36	176.90
	Level 10	24	224.85
	Total	361	

Test Statistics[a,b]

	rating
Kruskal-Wallis H	22.333
df	9
Asymp. Sig.	.008

a. Kruskal Wallis Test

b. Grouping Variable: group_level_588

Further, a post hoc test can help to determine where any differences lie between these levels. Pairwise Comparisons in Table 3.9 reveals that it was the significant differences in ratings between Level 1 and Level 7 (Adj. sig[15] = 0.015<0.05) and that between Level 1 and Level 10 (Adj.sig = 0.031<0.05) that results in an overall difference in all levels. Full results were presented in Appendix 3.

Table 3.9 - Pairwise Comparisons

[15] This is the adjusted p-value, which is obtained by multiplying the significance column by the number of comparisons so that it can be compared directly to 0.05. The difference is considered statistically significant when the adjusted p-value is less than 0.05.

Pairwise Comparisons of group_level_588

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
1-2	-23.384	21.963	-1.065	.287	1.000
1-3	-25.887	21.484	-1.205	.228	1.000
1-8	-35.600	23.152	-1.538	.124	1.000
1-9	-37.503	22.137	-1.694	.090	1.000
1-5	-44.468	21.796	-2.040	.041	1.000
1-4	-58.100	22.320	-2.603	.009	.416
1-6	-59.674	22.513	-2.651	.008	.362
1-7	-79.447	22.137	-3.589	<.001	.015
1-10	-85.454	25.150	-3.398	<.001	.031

Overall, the achievement of Objective 2 indicates that customer satisfaction is different among different levels of Face Serums, especially between Level 1 and Level7, and Level 1 and Level 10.

(3) Objective 3

Research Objective 3 is *to analyze whether a certain association exists between customer satisfaction and levels of Face Serums.*

As identified in the solution of Objective 2, product ratings are not normally distributed, thus the Ordinal Regression analysis was adopted. Data has passed four assumptions noted in §3.5.1.3. A2-1 and A2-2 were passed with the *level* being an ordinal dependent variable, and the *rating* is the continuous independent variable. A2-3 is to make sure that no multicollinearity[16] between independent variables when you have two or more of them. However, in our case *rating* is the only independent variable, so there is no multicollinearity (A2-3) to be tested. Table 3.10 provides results for the parallel regression assumption (A2-4), where sig = 0.718 > 0.05, indicating that each independent variable has an identical effect at each cumulative split of the ordinal dependent variable. So, the data also passed the fourth assumption.

Table 3.10 - Test the parallel regression assumption

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	666.924			
General	661.560[b]	5.365[c]	8	.718

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

a. Link function: Logit.

b. The log-likelihood value cannot be further increased after maximum number of step-halving.

c. The Chi-Square statistic is computed based on the log-likelihood value of the last iteration of the general model. Validity of the test is uncertain.

[16] Multicollinearity means several independent variables in a model are correlated.

Ordinal Regression analysis measured the association between dependent variable *level* and independent variable *rating*. As shown in Table 3.11, the model with the inclusion of the independent variable *rating* has a smaller likelihood ratio than with only the constant term (666.924 < 671.322) and this inclusion was statistically significant (sig. = 0.036 <0.05). It could be explained that *rating* could be the predictor of the *level* of *Face Serums.*

Table 3.11 - Model evaluation of ordinal regression analysis

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	671.322			
Final	666.924	4.398	1	.036

Link function: Logit.

More precisely, Table 3.12 indicates that every unit increase in *rating* (expressed in 0.01) was associated with an increase in the odds of the products falling at a higher level, with an odds ratio of exp (0.403) =1.496 (95% CI, 1.196 to 1.357), and p = .038 < 0.05. In other words, the 0.01 increase in *rating* was associated with a 49.6% increased probability of a product falling at a higher level. *Rating* is a positive predictor.

To conclude, the *rating* is a positive predictor of *level*, and each unit increase in *ratings* was associated with a 49.6% increased probability of a product belonging to a higher level.

Table 3.12 - Parameter Estimates for Ordinal Regression

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[group_level_588 = 1]	.019	.899	.000	1	.983	-1.742	1.781
	[group_level_588 = 2]	.706	.897	.618	1	.432	-1.053	2.464
	[group_level_588 = 3]	1.247	.899	1.926	1	.165	-.514	3.008
	[group_level_588 = 4]	1.656	.900	3.383	1	.066	-.109	3.421
	[group_level_588 = 5]	2.082	.903	5.317	1	.021	.312	3.851
	[group_level_588 = 6]	2.479	.905	7.498	1	.006	.705	4.253
	[group_level_588 = 7]	2.957	.909	10.587	1	.001	1.176	4.738
	[group_level_588 = 8]	3.482	.913	14.536	1	<.001	1.692	5.272
	[group_level_588 = 9]	4.514	.928	23.638	1	<.001	2.694	6.333
Location	rating	.403	.194	4.307	1	.038	.022	.784

Link function: Logit.

3.5.4 Answering Research Question 2

Again, guidance from §3.5.2 was followed to answer Research Question 2 stated in §1.3.: *Can customer sentiments towards Face Serums at different levels be extracted from all current textual reviews of Face Serums?* In this attempt, Research Objective 4 and 5 was achieved.

A summary of data collection was made in Table 3.13 and the full dataset will be supplied on demand. There were 5269 pieces of a product review of *Face Serums* at different levels being collected, which exceeds the expectation as more reviews were created during the two single points of time of secondary data collection. Level 1 contains the greatest number of reviews.

Table 3.13 - Data collection results for Question 2

Level	Actual	Expectation
L1	2304	2086
L2	597	508
L3	406	369
L4	324	281
L5	436	374
L6	165	145
L7	487	398
L8	122	127
L9	290	269
L10	138	124
Sum	5269	4681

As shown in Figure 3.2, Figure 3.3, and Figure 3.4, these 5269 pieces of textual reviews were created from 2011 to 2022, with the largest number of reviews falling in 2020 and 2021, in the first and the second seasons, and specifically, in February, March and April. As shown in Figure 3.5, the majority of reviewers (4031) wrote a short comment with a rating of 5, nevertheless, there were also a few reviewers (150) seem to be extremely unsatisfied.

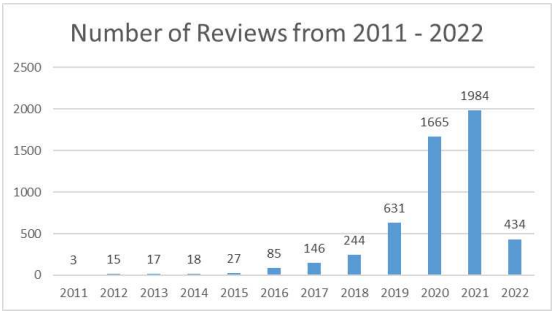


Figure 3.2 - Number of reviews by year

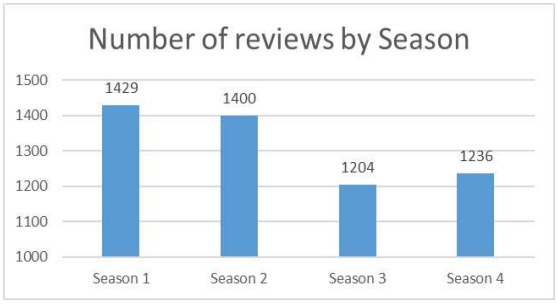


Figure 3.3 - Number of reviews by season

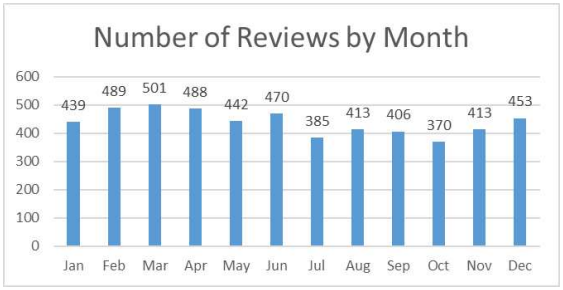


Figure 3.4 - Number of reviews by month

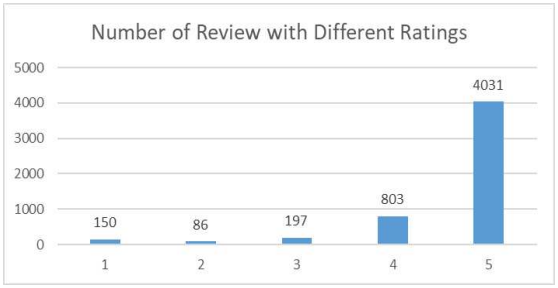


Figure 3.5 - Number of reviews with different ratings

(4) Objective 4

Research Objective 4 is *to determine general and emotional keywords and identify them.*

General keywords identified from textual reviews were presented in Table 3.14**.** Holistically, *product, time, price (money), texture (cream, oil), smell, package (bottle, capsule),* ingredients (*vitamins*) and effects of use (*difference),* area of use (*skin, face, eye),* frequency of use (*morning* and *night),* duration of use (*day, week, month, year*) are the factors that customers like to comment on about *Face Serums*. Interestingly, functions related to *spots, moisture, redness, tan, glow,* and special like were also reflected in keywords. The priority of these factors may vary across levels, for example, *price* is more frequently mentioned in Level 1, and *packages* noted as a "*bottle*", were frequently mentioned in Level 3, Level 4, and Level 5. Nevertheless, at an overall level, *product, time, price, textual smell, and difference* are the most concern by customers**.**

Table 3.14 - General product keywords

NO.	Overall	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10
1	product	product	product	skin	product	skin	product	skin	skin	product	product
2	skin	skin	skin	product	skin	product	skin	product	product	skin	skin
3	serum	use	serum	serum	serum	serum	serum	serum	feel	serum	serum
4	use	week	feel	use	feel	feel	feel	feel	serum	feel	feel
5	feel	feel	use	feel	smell	use	use	use	use	use	use
6	week	day	day	oil	use	face	love	night	capsule	night	day
7	day	serum	week	love	week	week	time	week	face	day	smell
8	face	time	face	smell	love	difference	day	day	difference	difference	night
9	difference	difference	difference	face	day	morning	smell	love	day	week	face
10	time	price	time	day	face	time	week	difference	night	love	cream
11	love	face	morning	time	morning	night	spot	year	love	face	week
12	night	eye	price	week	time	smell	result	morning	result	price	result
13	price	night	love	foundation	glow	day	night	time	line	morning	price
14	morning	love	result	texture	difference	texture	face	face	year	time	time
15	result	morning	night	bottle	vitamin	month	line	month	price	result	oil
16	month	result	moisturiser	makeup	tan	love	year	look	week	oil	line
17	year	month	texture	look	night	bottle	morning	texture	month	look	year
18	texture	spot	line	difference	bottle	way	price	price	bit	line	texture
19	smell	acid	year	way	look	year	dash	result	beauty	texture	money
20	oil	oil	month	morning	year	look	redness	line	smell	capsule	love

Emotional keywords were presented in Table 3.15. Top five keywords with positive and negative emotion polarity from reviews of overall and different levels. One can observe that reviewers feeling good about the products would consider "recommending" the products to others and especially in a premium group like Level 8 and Level 10, customers may feel "worth" buying the *Face Serums* even though these products are expensive; On the contrast, customers who had bad feelings tend to complain that *Face Serums* were "irritate" and "dull" and they may choose to quit using the products which disappoint them.

Table 3.15 - Keywords with positive and negative sentiment polarity

NO.	Overall	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10
Positive (Score > 0)											
1	love	love	love	love	love	love	love	love	love	love	love
2	good	good	good	good	like	like	like	great	like	like	recommend
3	like	great	great	like	good	good	recommend	like	good	recommend	worth
4	great	recommend	like	great	great	great	great	recommend	recommend	good	good
5	recommend	help	recommend	lovely	lovely	recommend	good	good	worth	great	great
Negative (Score < 0)											
1	leave	leave	leave	leave	leave	leave	leave	leave	leave	leave	leave
2	drop	bad	irritate	drop	drop	bad	suffer	drop	irritated	suffer	drop
3	suffer	suffer	drop	irritate	irritate	suffer	problem	stop	disappear	drop	damage
4	bad	drop	stop	problem	stop	drop	irritated	dull	disappointed	disappointed	problem
5	stop	stop	suffer	suffer	fake	disappoint	disappointed	irritate	nervous	pay	prevent

(5) Objective 5

Research Objective 5 was *to identify the customer sentiments polarity for Face Serums at different levels.*

The sentiment polarity score of each group was automatically calculated by Textblob[17] developed in Python, as described in §3.5.2.3. Table 3.16 represents the original sentiment polarity scores calculated based on three dimensions: each sentence of the review, a whole piece of review, and a whole group of reviews from each level. In addition, the medium and mean of ratings from each level are also provided for comparison. As one might observe from Table 3.16 customers show positive sentiment polarity to all levels with all sentiment polarity scores larger than zero. Specifically, sentiment polarity scores are relatively higher in Level 6 and Level 7, with the score calculated by three dimensions being 0.25 and 0.26, 0.28 and 0.31, and 0.26 and 0.26. To make the values more comparable, sentiment polarity scores and ratings were transferred into a standardized z-score. For example, the standardized mean rating of Level 7 is 1.67.

Table 3.16 - Original sentiment polarity and standardized value

Original value VS standardized value (z-score)										
Level	1-SENTENCE	z-score	2-REVIEW	z-score	3-GROUP	z-score	Medium of ratings	z-score	Mean of ratings	z-score
L1	0.20	-1.94	0.23	-1.79	0.20	-2.07	4.59	-1.27	4.49	-1.60
L2	0.22	-0.76	0.25	-0.80	0.22	-0.89	4.62	-1.05	4.55	-0.84
L3	0.24	0.41	0.27	0.20	0.24	0.30	4.58	-1.30	4.58	-0.47
L4	0.24	0.41	0.27	0.20	0.23	-0.30	4.88	0.55	4.65	0.42
L5	0.24	0.41	0.27	0.20	0.23	-0.30	4.79	-0.04	4.63	0.16
L6	0.25	1.00	0.28	0.70	0.26	1.48	5.00	1.29	4.61	-0.09
L7	0.26	1.59	0.31	2.19	0.26	1.48	5.00	1.29	4.75	1.67
L8	0.23	-0.18	0.25	-0.80	0.24	0.30	4.71	-0.50	4.55	-0.84
L9	0.22	-0.76	0.26	-0.30	0.23	-0.30	4.75	-0.25	4.61	-0.09
L10	0.23	-0.18	0.27	0.20	0.24	0.30	5.00	1.29	4.75	1.67

Standardized values in Table 3.16 were visualized in Figure 3.6. It could be identified that Level 7 has the best performance than other levels, with all of the sentiment polarity scores, as well as the customer ratings, being at the top.

[17] TextBlob is a simple Python library that help to calculate the sentence sentiment polarity.

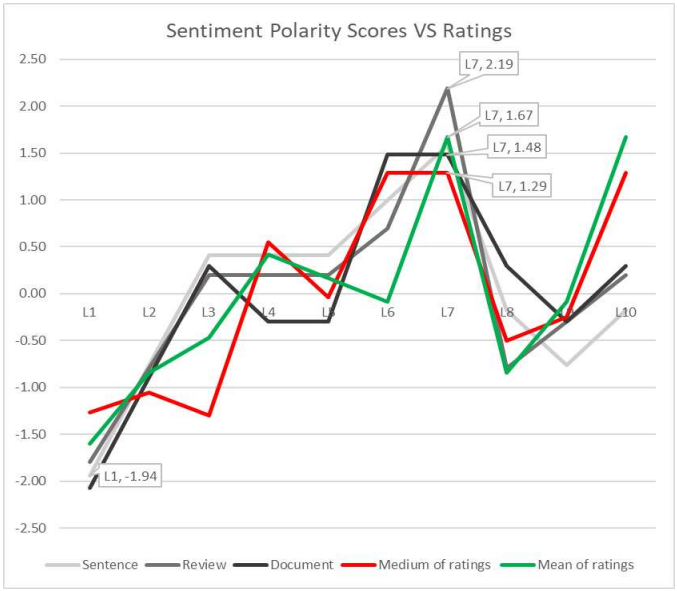


Figure 3.6 - Sentiment Polarity Scores VS Ratings

Table 3.17 - Friedman Test

Test Statistics[a]

N	10
Chi-Square	.560
df	4
Asymp. Sig.	.967

a. Friedman Test

An additional effort was made to examine the difference between the sentiment polarity scores and rating scores using a multi-sample Friedman test[18]. In Table 3.17, sig. = 0.967 > 0.05, indicating that there was no statistically significant difference in sentiment polarity scores based on each sentence of the review, a whole piece of review, and a whole group of reviews, as well as the Medium and Mean of ratings from each level.

[18] The Friedman test is used to test for differences between groups when the dependent variable being measured is ordinal or continuous level .(Laerd Statistics, 2022a)

3.6 Case study lecture slides





ISCTE

Pedagogical Case study

Content

Background

About LOOKFANTASTIC®

Case Questions

Case Resolution

Discussion

Sep 2022

ISCTE

Background

What is Customer Experience?

A multidimensional conctruct during purchasing journey

Prepurchase → **Purchase** → **Postpurchase**

- Cognitional
- Emotional
- Behavioral
- Sensorial
- Social

Response →

- Firm
- Firm's offerings e.g. product, service, brand

ISCTE Background

How to measure Customer Experience?

Classic survey-based approaches

Examples:
Service Quality - SERVQUAL scale,
Customer Satisfaction - EDM model
Customer experience models

- Confusion in survey questions
- Complicated scale
- Time-comsuming and labour-intensive

User-generated content approaches

Examples:
Online reviews (**e-commerce reviews,**
third party reviews, social media)

- Free of bias from survey
- Simple
- Accessible
- Understandable & transaction-specific
- Large-scale of data

ISCTE About LOOKFANTASTIC®

Who is LOOKFANTASTIC® ?

lookfantastic

29
Europe's number one online premium beauty retailer with 29 localized sites

660+
7 product categories,
660 premium brands,
22,000 products,
shipping to over 200 countries

588
588 **Face Serums** from 180 Skincare brands

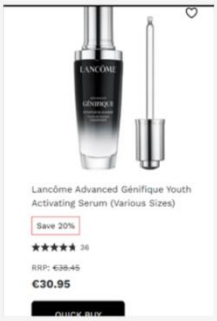
Face Serums



ISCTE About LOOKFANTASTIC®

Where to check customer reviews?

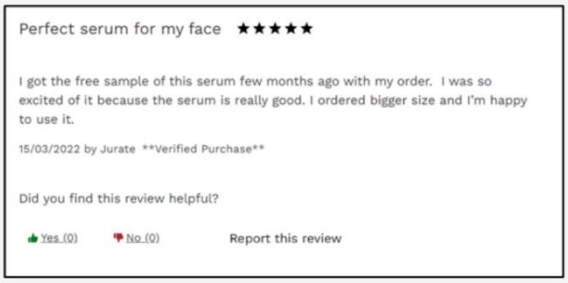
Example 1



Example 2



Example 3



ISCTE Case Questions

Research Question 1

PERCEPTION

What is the association between customer satisfaction and the price levels of Face Serums, based on all current product ratings of Face Serums?

- **Objective 1:** To classify Face Serums into different levels.
- **Objective 2:** To analyze whether customer satisfaction is different among different levels of Face Serums.
- **Objective 3:** To analyze whether a certain association exists between customer satisfaction and levels of Face Serums.

Research Question 2

EMOTION

Can customer sentiments towards Face Serums at different levels be extracted from all current textual reviews of Face Serums?

- **Objective 4:** To determine general and emotion keywords and identify them.
- **Objective 5:** To identify the customer sentiments polarity for Face Serums at different levels.

Methods Guidance

Stages		Research Question 1			Research Question 2		
		Tasks	Software	Tool	Tasks	Software	Tools
1	Data collection & data storage	Web crawling name, price, rating and number of reviews	Python	Respects Beautiful Soup Pandas	Manually collect title, body, date and rating of all reviews	Excel	
2	Data processing	Remove unrelated products, duplicates, currency lables and split variables	Excel	Excel fuctions	6 text pre-processing tasks	Python	xlrd, nltk, re
3	Data analysis	Objective 1	Spss	"Frequency" and "Transform"	Objective 4	Python	Sentiment Analysis dictionary: AFINN-111
		Objective 2	Spss	ANOVA test or Kruskal-Wallis H test	Objective 5	Python	Sentiment Analysis library: Textblob
		Objective 3	Spss	ANOVA test or Ordinal Logistic Regression Analysis			

Results Report

588 Face Serums, 361 reviewed in form of both numeric ratings and short comments

Objective 1	588 Face Serums are grouped in 10 levels with equal percentile (10%)
Objective 2	Significant differences of ratings were found between Level 1 and Level 7, and Level 1 and Level 10
Objective 3	Rating is a positive predictor and each unit increase in ratings was associated with a 49.6% increased probability of a product belonging to a higher level.

5269 pieces of a product review of Face Serums

Objective 4	Product, time, price (money), texture (cream, oil), smell, package (bottle, capsule), ingredients (vitamins) and effects of use (difference), area of use (skin, face, eye), frequency of use (morning and night), duration of use (day, week, month, year) are key factors
Objective 5	Highest sentiment score in Level 6 & 7, lowest in Level 1. Similar to ratings.

Resarch Objective 1 - Group into Ten Levels

Case Resolution



Level	Percentiles	Minimum	Maximum	Representative Brands
1	0-10%	3.45	11.45	The Ordinary, Revolution
2	10%-20%	12.27	20.96	The Ordinary, Clinique, BeautyPro
3	20%-30%	21.45	32.95	Pixi, Vichy
4	30%-40%	33.27	41.95	Antipodes, Eucerin, Medik8
5	40%-50%	42.95	50.95	Ecooking, Medik8
6	50%-60%	50.97	62.45	DECLÉOR, AHAVA
7	60%-70%	62.95	75.45	Lancôme, Filorga, Dermalogica
8	70%-80%	76.45	94.95	ALGENIST, Dr Dennis, Elizabeth Arden, Gatineau, Murad
9	80%-90%	95.34	124.45	Avant, Estée Lauder, Perricone MD
10	90%-100%	124.9	429.45	Chantecaille, RéVive,111SKIN, Dermalogica, Darphin, La Mer

Resarch Objective 2 - Kruskal-Wallis Test

Case Resolution

Ranks

	group_level_588	N	Mean Rank
rating	Level 1	50	139.40
	Level 2	37	162.78
	Level 3	40	165.29
	Level 4	35	197.50
	Level 5	38	183.87
	Level 6	34	199.07
	Level 7	36	218.85
	Level 8	31	175.00
	Level 9	36	176.90
	Level 10	24	224.85
	Total	361	

Pairwise Comparisons of group_level_588

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
1-2	-23.384	21.963	-1.065	.287	1.000
1-3	-25.887	21.484	-1.205	.228	1.000
1-8	-35.600	23.152	-1.538	.124	1.000
1-9	-37.503	22.137	-1.694	.090	1.000
1-5	-44.468	21.796	-2.040	.041	1.000
1-4	-58.100	22.320	-2.603	.009	.416
1-6	-59.674	22.513	-2.651	.008	.362
1-7	-79.447	22.137	-3.589	<.001	.015
1-10	-85.454	25.150	-3.398	<.001	.031

Test Statistics[a,b]

	rating
Kruskal-Wallis H	22.333
df	9
Asymp. Sig.	.008

a. Kruskal Wallis Test

b. Grouping Variable: group_level_588



Resarch Objective 3 - Ordinal Regression Analysis

Case Resolution

Test of Parallel Lines[a]

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	666.924			
General	661.560[b]	5.365[c]	8	.718

The null hypothesis states that the location parameters (slope coefficients) are the same across response categories.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	671.322			
Final	666.924	4.398	1	.036

Link function: Logit.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Threshold	[group_level_588 = 1]	.019	.899	.000	1	.983	-1.742	1.781
	[group_level_588 = 2]	.706	.897	.618	1	.432	-1.053	2.464
	[group_level_588 = 3]	1.247	.899	1.926	1	.165	-.514	3.008
	[group_level_588 = 4]	1.656	.900	3.383	1	.066	-.109	3.421
	[group_level_588 = 5]	2.082	.903	5.317	1	.021	.312	3.851
	[group_level_588 = 6]	2.479	.905	7.498	1	.006	.705	4.253
	[group_level_588 = 7]	2.957	.909	10.587	1	.001	1.176	4.738
	[group_level_588 = 8]	3.482	.913	14.536	1	<.001	1.692	5.272
	[group_level_588 = 9]	4.514	.928	23.638	1	<.001	2.694	6.333
Location	rating	.403	.194	4.307	1	.038	.022	.784

Link function: Logit.

Resarch Objective 4 - General Wordcloud

Case Resolution



Research Objective 4 (Continued) - General Keyworks and Emotial Keyworks

NO.	Overall	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10
1	product	product	product	skin	product	skin	product	skin	skin	product	product
2	skin	skin	skin	product	skin	product	skin	product	product	skin	skin
3	serum	use	serum	serum	serum	serum	serum	serum	feel	serum	serum
4	use	week	feel	use	feel	feel	feel	feel	serum	feel	feel
5	feel	feel	use	feel	smell	use	use	use	use	use	use
6	week	day	day	oil	use	face	love	night	capsule	night	day
7	day	serum	week	love	week	week	time	week	face	day	smell
8	face	time	face	smell	love	difference	day	day	difference	difference	night
9	difference	difference	difference	face	day	morning	smell	love	day	week	face
10	time	price	time	day	face	time	week	difference	night	love	cream
11	love	face	morning	time	morning	night	spot	year	love	face	week
12	night	eye	price	week	time	smell	result	morning	result	price	result
13	price	night	love	foundation	glow	day	night	time	line	morning	price
14	morning	love	result	texture	difference	texture	face	face	year	time	time
15	result	morning	night	bottle	vitamin	month	line	month	price	result	oil
16	month	result	moisturiser	makeup	tan	love	year	look	week	oil	line
17	year	month	texture	look	night	bottle	morning	texture	month	look	year
18	texture	spot	line	difference	bottle	way	price	price	bit	line	texture
19	smell	acid	year	way	look	year	dash	result	beauty	texture	money
20	oil	oil	month	morning	year	look	redness	line	smell	capsule	love

Case Resolution

NO.	Overall	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	Level 7	Level 8	Level 9	Level 10
	Positive (Score > 0)										
1	love	love	love	love	love	love	love	love	love	love	love
2	good	good	good	good	like	like	like	great	like	like	recommend
3	like	great	great	like	good	good	recommend	like	good	recommend	worth
4	great	recommend	like	great	great	great	great	recommend	recommend	good	good
5	recommend	help	recommend	lovely	lovely	recommend	good	good	worth	great	great
	Negative (Score < 0)										
1	leave	leave	leave	leave	leave	leave	leave	leave	leave	leave	leave
2	drop	bad	irritate	drop	drop	bad	suffer	drop	irritated	suffer	drop
3	suffer	suffer	drop	irritate	irritate	suffer	problem	stop	disappear	drop	damage
4	bad	drop	stop	problem	stop	drop	irritated	dull	disappointed	disappointed	problem
5	stop	stop	suffer	suffer	fake	disappoint	disappointed	irritate	nervous	pay	prevent

Resarch Objective 5 - Sentiment Analysis

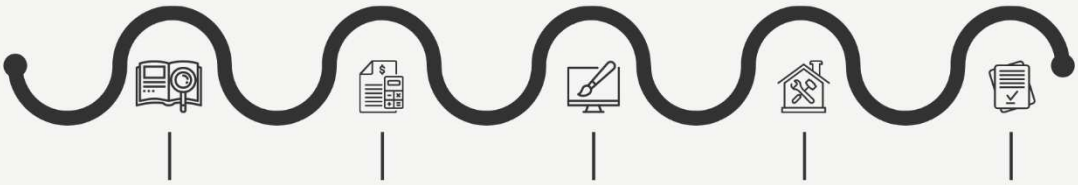
Original value VS standardized value (z-score)										
Level	1-SENTENCE	z-score	2-REVIEW	z-score	3-GROUP	z-score	Medium of ratings	z-score	Mean of ratings	z-score
L1	0.20	-1.94	0.23	-1.79	0.20	-2.07	4.59	-1.27	4.49	-1.60
L2	0.22	-0.76	0.25	-0.80	0.22	-0.89	4.62	-1.05	4.55	-0.84
L3	0.24	0.41	0.27	0.20	0.24	0.30	4.58	-1.30	4.58	-0.47
L4	0.24	0.41	0.27	0.20	0.23	-0.30	4.88	0.55	4.65	0.42
L5	0.24	0.41	0.27	0.20	0.23	-0.30	4.79	-0.04	4.63	0.16
L6	0.25	1.00	0.28	0.70	0.26	1.48	5.00	1.29	4.61	-0.09
L7	0.26	1.59	0.31	2.19	0.26	1.48	5.00	1.29	4.75	1.67
L8	0.23	-0.18	0.25	-0.80	0.24	0.30	4.71	-0.50	4.55	-0.84
L9	0.22	-0.76	0.26	-0.30	0.23	-0.30	4.75	-0.25	4.61	-0.09
L10	0.23	-0.18	0.27	0.20	0.24	0.30	5.00	1.29	4.75	1.67



Case Resolution

ISCTE Discussion

In class discussion: How to apply the customer insights?



Market Research

Marketing Campaign

Product Development

HR: Digital skills development

Customer Relationship Management

ISCTE

Abbreviations

- ANOVA - Analysis of Variance
- EDM - Expectancy-Disconfirmation Model
- HR - Human Resource



Thank you

For your attention

4 Discussion and Conclusion

The purpose of this thesis is to access customer perception and sentiment based on online reviews, which serves as a training programme targeting master's students in a business area. For this purpose, the author obtained two types of reviews of *Face Serums* available on the case LOOKFANTASTIC® to answer two research questions, during which five research objectives were achieved, yielding several groups of findings and contributions.

4.1 Findings

The first research question is *What is the association between customer satisfaction and the price levels of Face Serums, based on all current product ratings of Face Serums?* The achievement of Research Objective 1, 2, and 3 contributed to the answer to this question.

Research Objective 1 *is to classify Face Serums into different levels.* At this stage, 588 Face Serums were classified into ten price levels with equal percentiles (10%). The results indicated that each level is in a different price range and has its most representative brands. Although *Face Serums* can be sold for up to 400 euros, a majority (80%) of them sell for less than 100 euros. The products from affordable levels to high-end levels form a highly differentiated portfolio of *Face Serums in* the case LOOKFANTASTIC®.

Research Objective 2 is *to analyze whether customer satisfaction is different among different levels of Face Serums.* The results of Kruskal-Wallis H-test indicated that customer satisfaction is not the same across all these levels of *Face Serums,* and in particular, the most significant differences were found between Level 1 and Level 7, and between Level 1 and Level 10. Holistically speaking, Level 7 and Level 10, represented by brands like *Chantecaille, RéVive, Sepai, Filorga, Lancôme, and Shiseido,* have better customer satisfaction than Level 1, represented by such as *The Ordinary, The INKEY, and Revolution.*

Research Objective 3 is *to analyze whether a certain association exists between customer satisfaction and levels of Face Serums.* It was found hard to find the linear correlation between customer satisfaction and price levels, but the results of Ordinal Regression Analysis indicated that rating is still a positive predictor of the level of Face Serums, and specifically, a single unit increase in rating was associated with the 49.6% increased probability of a *Face Serums* falling into a higher level. In other words, a more expensive *Face Serum* is not necessarily more satisfying, but a more satisfying *Face Serum* is more likely to be an expensive product.

So, the answer to the first research question is that the association between customer satisfaction and product level is not necessarily a linear correlation as usually expected, but customer satisfaction is still a positive predictor of product level in this case study.

The second research question is *Can customer sentiments towards Face Serums at different levels be extracted from all current textual reviews of Face Serums?* The achievement of Research Objective 4 and 5 contributed to the answer to this question.

Research Objective 4 is *to determine general and emotional keywords and identify them.* The fourth group of findings yielded from textual analysis, which is the use of the computer to replace humans in reading and calculating the frequency of keywords. The extraction of general keywords suggested key factors of *Face serums* that customers might concern about. One group of keywords captured product-wise features, including *price, texture, smell, ingredient, package,* and *function*. Another group of keywords captured the experience of using the *Face Serums*, including *the effect of use*, *the area of use*, *the frequency of use,* and the *duration of use*. It was also found that the priority of these factors varies from different levels of Face Serums. The extraction of emotional keywords indicates that different customer emotions generated from past experiences may lead to different shopping behaviours in the future. When customers have a positive feeling, they tend to *recommend* the *Face Serums* to others, while those who feel bad about the purchase, tend to complain and give up using the *Face Serums.*

Research Objective 5 is *to identify the customer sentiments polarity for Face Serums at different levels.* This group of findings yields from the calculation of sentiment polarity scores using Dictionary-based sentiment analysis. Level 6 and Level 7 have the most positive sentiment from customers, but Level 7 also has the highest customer satisfaction. In contrast, Level 1 has relatively less positive sentiment and this is similar to its performance in terms of customer satisfaction. Additionally, multi-sample Friedman was used to test the validity of sentiment score by comparing it with the quantitative data, *rating.* The results showed that the calculation is valid to some extent and also suggested that it is likely to predict customer sentiments using online ratings.

So far, the answer to the second research question is that customer sentiment could be extracted from textual review using text analysis techniques, and customer sentiment polarity might even be reflected by customer ratings.

Other critical findings also emerged from the two data collection phases. Firstly, web crawling was designed to be used as an alternative to manual data collection in this case study. Theoretically, by writing several lines of code in Python, all the data required could be scraped from the web page at once. However, the implementation of web scraping was not always going

so well in practice, which might be caused by the anti-scraping mechanism. In response to this issue, the author intervened in this data collection process as well. Secondly, data of unexpected products are often mixed with the targeted products*, Face Serums*. This kind of mix was mainly caused by the inaccurate product classification of the search engine on LOOKFANTASTIC® International. So additional efforts were made to data cleaning. Thirdly, the review system does not provide an attribute-wise rating, which needs to be improved in the future. Additionally, it was interesting to find that the number of short comments varies by year, by month, and by season. The 2022 and 2021 have seen a sharp increase in the number of reviews, and generally, the first half of the year usually concentrates more reviews than the second half. The vast majority of reviewers gave a 5-star rating.

4.2 Implications

This case study with pedagogical purpose has a number of methodological, theoretical, and managerial contributions. The first, and also the most important methodological contribution is that this pedagogical case study provides a modularized case solution supported by a comprehensive literature review and practical guidance. The target audiences, master students, might be able to better define the customer experience and its related components, recognize some classic and new approaches to accessing customer experience and use multiple techniques to obtain and analyze quantitative and qualitative data following the guidance. The master students might not only be equipped with a group of digital skills, but more importantly, they might be able to navigate business challenges by immersing in real-world scenarios.

The second contribution to theory is that the thesis explored how both quantitative and qualitative online reviews could be used to access the components of customer experience, especially in online beauty retail. Extant literature has extensively highlighted the importance of online reviews thus far, however, the combined use of both types of reviews has remained unexplored. Thus, the current contribution is unique in the context of the online beauty retail context. On the other hand, the above is also a methodological contribution to customer experience measurement. Studies in the field of customer experience were majorly survey-based, which are complicated, labour-intensive, and time-consuming. This is the pioneering study that leverages user-contributed data in measurement, thus contributing to the literature.

Another theoretical contribution is that this thesis provides a group of attributes of the specific category of products, *Face Serums*. Extant literature has explored products or service attributes of a whole sector, such as in hospitality and healthcare ecommerce, or of a certain type of product, such as beer and mobile phones. However, the most concerning attributes of

Face Serums have not been explored yet. Specific knowledge of such attributes would help other researchers focusing on *Face Serums* or even similar skincare products to develop their study in Customer Experience.

As regards the managerial contribution: The primary managerial implication of this study lies in Product Development or Marketing. The development of classification standards helps the managers to determine the marketing positioning of their *Face Serums* and identify their competitors more precisely. This might help, for example, the practitioners to learn from leading *Face Serums* while learning the lessons from the most unsatisfying ones. The thesis also provides insights into the area of product pricing. In terms of *Face Serums*, the low-price strategy might not be advisable for such a skincare product, or managers should at least not reduce investments in other aspects, such as branding and packaging, in exchange for lower prices. Other contributions lie in the design of product attributes. The product-wise and product usage features determined in this thesis could contribute to the investment decision and resource allocation during the product design and marketing campaign.

The second managerial contribution lies in Customer Relation Management. Our case study suggests that online satisfaction ratings could reflect customer sentiments, which is important for ecommerce managers in Customer Service or Membership Management to manage the customer reviews and design the communication strategy accordingly.

Finally, this study also promotes managers to have more flexible use of digital skills. Ecommerce firms crunch huge sets of data and well-developed analytical engines provide much convenience for managers but may not meet their needs in all situations. It has been suggested that marketing managers should combine digital skills with their professional experience to capture more marketing information in a dynamic ever-changing world. This thesis is a pioneer that provides a real case along with technical practical guidance, which enables the managers to easily apply these digital skills in their daily work.

4.3 Limitations and future scope

This study is subject to several limitations. Firstly, the results did not suggest the weights of product attributes in affecting customer experience and how the weights of the attributes vary depending on different levels of *Face Serums.* Future research can bring insights into this field. Secondly, we did not explore the demographic characteristics and psychological mechanism of the customer and the moderating effect of these variables due to a lack of data. These can be studied by future researchers. Thirdly, this study only focused on a single type of skincare product, thus future research could also be expanded to similar categories, such as cream, and

lotion. This study assessed two well-developed aspects of customer experience, which serve as the building block of customer experience management. But future research could be expanded on behavioral, sensorial, and social responses components of customer experience. Additionally, while using online reviews makes the data collection and information generation easier, it should be reminded that online reviews may not be a true representative of the customer sample. Future researchers may try to overcome this limitation by including customer reviews from multiple channels. And lastly, with the purpose of educating entry-level audiences, this study only applied the simplest Dictionary-based sentiment analysis. Future research can fully tap into the online review database created by this thesis using Machine learning and more advanced text mining methods.

4.4 Conclusion

This pedagogical case study addressed two research questions relating to consumer perception and sentiment respectively, based on online reviews data collected from the case company LOOKFANTASTIC®, aiming to educate master students in the business area to access customer experience using digital tools. Overall, it was found that online rating is a positive predictor of product level and customer sentiments could be extracted from textual reviews. This study has plenty of contributions that it provides modularized pedagogical case solutions, combines quantitative and qualitative user-generated data, extracts product-specific attributes, and also the customer perception and sentiment insights that might contribute to Product Development, Marketing, and Customer Relationship Management. This thesis also has some limitations that it has not explored the weights of product attributes, the psychological, cultural, and Socioeconomic background as well as the behavioral, sensorial, and social responses components of customer experience due to the lack of data. Also, online reviews may not be a good representative of the customer sample, but this case study serves as a good example. Future research can bring more insights into these fields.

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6 Appendices

Appendix 1 – List of Face Serums on LOOKFANTASTIC

brand	name	volume(ml)	price per €/30ml	price(€)	rating	reviews
The Ordinary		30	3.45	3.45	4.6	50
The Ordinary	The Ordinary Retinol Serum 0.2% in Squalane 30ml	30	4.95	4.95	4.64	11
The Ordinary	The Ordinary Salicylic Acid 2% Solution 30ml	30	4.95	4.95	3.63	8
The Ordinary	The Ordinary Niacinamide 10% + Zinc 1% High Strength Vitamin and Mineral Blemish Formula 30	30	5.95	5.95	4.55	346
The Ordinary	The Ordinary Vitamin C Suspension 23% + HA Spheres 30ml	30	5.95	5.95	4.08	60
The INKEY	The INKEY List Q10 Serum 30ml	30	5.95	5.95	4.59	29
The Ordinary	The Ordinary Retinol Serum 0.5% in Squalane 30ml	30	5.95	5.95	5	27
The Ordinary	The Ordinary 100% Plant-Derived Squalane 30ml	30	6.45	6.45	4.43	63
The Ordinary	The Ordinary Azelaic Acid Suspension 10% 30ml	30	6.45	6.45	4.56	50
The Ordinary	The Ordinary Hyaluronic Acid 2% + B5 Hydration Support Formula 30ml	30	6.95	6.95	4.69	450
The Ordinary	The Ordinary Caffeine Solution 5% + EGCG 30ml	30	6.95	6.95	4.21	186
The Ordinary	The Ordinary Lactic Acid 10% + HA 2% Superficial Peeling Formulation 30ml	30	6.95	6.95	4.86	51
The INKEY	The INKEY List Hyaluronic Acid Serum 30ml	30	6.95	6.95	4.73	49
The Ordinary	The Ordinary 100% Organic Cold-Pressed Argan Oil 30ml	30	6.95	6.95	4.28	39
The Ordinary	The Ordinary Vitamin C Suspension Cream 30% in Silicone 30ml	30	6.95	6.95	3.83	36
The Ordinary	The Ordinary Lactic Acid 5% + HA 2% Superficial Peeling Formulation 30ml	30	6.95	6.95	4.71	24
The Ordinary	The Ordinary 10% Agireline Solution 30ml	30	6.95	6.95	4.15	20
The Ordinary	The Ordinary Retinol Serum 1% in Squalane 30ml	30	6.95	6.95	4.84	19
The Ordinary	The Ordinary Amino Acids + B5	30	6.95	6.95	4.44	18
The Ordinary	The Ordinary Mandelic Acid 10% 30ml	30	6.95	6.95	4.86	7
The Ordinary	The Ordinary Resveratrol Serum 3% + Ferulic Acid 3% 30ml	30	6.95	6.95	4.6	5
Revolution	Revolution Skincare Blemish and Pore Refining Serum - 10% Niacinamide + 1% Zinc	30	6.95	6.95	4.5	2
The Ordinary	The Ordinary AHA 30% + BHA 2% Peeling Solution 30ml	30	7.45	7.45	4.54	111
The Ordinary	The Ordinary Marine Hyaluronics 30ml	30	7.45	7.45	4.43	14
The INKEY	The INKEY List Niacinamide	30	7.95	7.95	4.58	12
The Ordinary	The Ordinary EUK 134 Serum 0.1% 30ml	30	7.95	7.95	4.9	10
Revolution	Revolution Skincare 3% Vitamin C Serum 30ml	30	8.45	8.45	no rating	no review
The Ordinary	The Ordinary Alpha Arbutin 2% + HA Concentrated Serum 30ml	30	8.45	8.45	4.24	38
Revolution	Revolution Skincare 0.3% Retinol with Vitamins and Hyaluronic Acid Serum	30	8.95	8.95	no rating	no review
The Ordinary	The Ordinary Magnesium Ascorbyl Phosphate Solution 10% 30ml	30	8.95	8.95	4.50	8
The Ordinary	The Ordinary Granactive Retinoid Serum 2% in Squalane 30ml	30	8.95	8.95	4.67	3
The INKEY	The INKEY List Vitamin C Serum 30ml	30	9.45	9.45	3.00	22
The INKEY	The INKEY List Lactic Acid Exfoliant 30ml	30	9.45	9.45	4.25	8
The Ordinary	The Ordinary 100% Pycnogenol 5% 15ml	15	19.90	9.95	4.69	29
Revolution	Revolution Skincare 0.5% Retinol Intense Serum	30	9.95	9.95	no rating	no review
Revolution	Revolution Skincare 12.5% Vitamin C Super Serum 30ml	30	10.45	10.45	no rating	no review
The Ordinary	The Ordinary Ascorbyl Glucoside Solution 12% 30ml	30	10.45	10.45	4.50	50
The INKEY	The INKEY List Collagen Booster 30ml	30	10.45	10.45	4.78	23
The Ordinary	The Ordinary Niacinamide 10% + Zinc 1% Supersize Serum 60ml	60	5.23	10.45	4.73	26
The Ordinary	The Ordinary Matrixyl 10% + HA High Strength Peptide Formulation 30ml	30	10.95	10.95	4.52	31
Salcura Antiac	Salcura Antiac Activ Gel Serum (15ml)	15	22.90	11.45	5.00	2
Revolution	Revolution Superdewy Make Up Serum 17ml	17	20.21	11.45	no rating	no review
Revolution	Revolution Skincare 15% Niacinamide Super Serum 30ml	30	11.45	11.45	no rating	no review
Revolution	Revolution Skincare CBD Serum 30ml	30	11.45	11.45	no rating	no review
Revolution	Revolution Skincare Cica Serum 30ml	30	11.45	11.45	no rating	no review
The INKEY	The INKEY List Retinol Serum 30ml	30	11.45	11.45	4.73	41
The INKEY	The INKEY List Beta Hydroxy Acid Exfoliant 30ml	30	11.45	11.45	4.17	6
Revolution	Revolution Skincare Gold Elixir 30ml	30	11.45	11.45	5.00	5
Revolution	Revolution Skincare Snow Mushroom Serum 30ml	30	11.45	11.45	4.67	3
Revolution	Revolution Skincare Turmeric Serum 30ml	30	11.45	11.45	4.00	2
ManCave	ManCave Age Defence Face Serum 50ml	50	6.87	11.45	no rating	no review
ManCave	ManCave Anti-Pollution Face Serum	50	6.87	11.45	no rating	no review
Revolution	Revolution Skincare Hydration Boost Night 50ml	50	6.87	11.45	no rating	no review
Revolution	Revolution Skincare Mattify Boost 50ml	50	6.87	11.45	no rating	no review
The Ordinary	The Ordinary Niacinamide 10% + Zinc 1% High Strength Vitamin and Mineral Blemish Formula Du	60	5.73	11.45	4.90	29
L'Oréal	L'Oréal Paris Hydra Genius Liquid Care Moisturiser Normal Dry Skin 70ml	70	4.91	11.45	4.00	7
Clinique	Clinique iD Active Cartridge Concentrate for Irritation	10	37.35	12.45	no rating	no review
Clinique	Clinique iD Active Cartridge Concentrate for Pores & Uneven Texture	10	37.35	12.45	no rating	no review
Clinique	Clinique iD Active Cartridge Concentrate for Uneven Skin Tone	10	37.35	12.45	no rating	no review
Clinique	Clinique iD Active Cartridge Concentrate for Lines & Wrinkles	10	37.35	12.45	5.00	3
Clinique	Clinique iD Active Cartridge Concentrate for Fatigue	10	37.35	12.45	5.00	1
Revolution	Revolution Skincare 1% Retinol Super Intense Serum	30	12.45	12.45	5.00	1
The Ordinary	The Ordinary Hyaluronic Acid 2% + B5 Supersize Serum 60ml	60	6.23	12.45	4.71	35
The Ordinary	The Ordinary "Buffet" Multi-Technology Peptide Serum 30ml	30	13.45	13.45	4.58	95
The Ordinary	The Ordinary Caffeine Solution 5% + EGCG Duo	30	13.45	13.45	4.38	8
Revolution	Revolution Skincare CBD Super Serum 30ml	30	13.95	13.95	no rating	no review
Revolution	Revolution Skincare Hydro Bank Hydrating Essence Serum	30	13.95	13.95	no rating	no review
Bulldog	Bulldog Age Defence Serum 50ml	50	8.37	13.95	5.00	5
The Ordinary	The Ordinary Hyaluronic Acid 2% + B5 Hydration Support Formula Duo 2 x 30ml	60	6.98	13.95	4.83	18
Antipodes	Antipodes Worship Skin Defence Antioxidant Serum 10ml	10	43.35	14.45	no rating	no review
Biologi	Biologi Bd Luminosity Face Serum 5ml	5	89.70	14.95	no rating	no review
Biologi	Biologi Bm Regenerate Anti-Ageing Serum 5ml	5	89.70	14.95	no rating	no review
Sukin	Sukin Super Greens Recovery Serum 30ml	30	15.95	15.95	4.11	9
The Ordinary	The Ordinary Alpha Arbutin 2% + HA Concentrated Serum Exclusive Duo	30	15.95	15.95	5.00	5
Green People	Green People Oy! Clear Skin Purifying Serum 30ml	30	15.95	15.95	4.00	1
Aesop	Aesop Control Serum 9ml	9	56.50	16.95	4.63	8
Revolution	Revolution Pro 24k Priming Serum 28ml	28	18.16	16.95	no rating	no review
BeautyPro	BeautyPro Brightening 10% Vitamin-C Daily Serum 30ml	30	16.95	16.95	no rating	no review
BeautyPro	BeautyPro Firming AHA & Enzyme Daily Serum 30ml	30	16.95	16.95	no rating	no review

BeautyPro	BeautyPro Hydrating 1% Hyaluronic Acid Daily Serum 30ml	30	16.95	16.95	no rating	no review
BeautyPro	BeautyPro Nourishing Squalene Daily Serum 30ml	30	16.95	16.95	no rating	no review
BeautyPro	BeautyPro Retinol 1% Overnight Serum 30ml	30	16.95	16.95	no rating	no review
BeautyPro	BeautyPro Revitalising Vitamin CAKE Daily Serum 30ml	30	16.95	16.95	no rating	no review
Oh K!	Oh K! Chok Chok Illuminating Serum 30ml	30	16.95	16.95	no rating	no review
Skin Republic	Skin Republic Skin Booster Hyaluronic Acid 1% and 2% Niacinamide Serum 30ml	30	16.95	16.95	no rating	no review
Skin Republic	Skin Republic Skin Booster Retinol and Squalene 1% Serum 30ml	30	16.95	16.95	no rating	no review
Skin Republic	Skin Republic Skin Booster Vitamin C 4% and 1.5% Alpha Arbutin Serum 30ml	30	16.95	16.95	no rating	no review
UpCircle	UpCircle Face Serum with Coffee 30ml	30	16.95	16.95	no rating	no review
The INKEY	The INKEY List- 15% Vitamin C and EGF Serum 30ml	30	16.95	16.95	4.48	21
The Ordinary	The Ordinary Ascorbyl Tetraisopalmitate Solution 20% in Vitamin F 30ml	30	16.95	16.95	4.62	13
The INKEY	The INKEY List Hepta-Peptide Serum 30ml	30	16.95	16.95	3.67	3
Natio	Natio Advanced Lifting and Firming Serum (30ml)	30	17.45	17.45	5.00	2
Bioderma	Bioderma Sébium Pore Refining Cream Combination to Oily Skin 30ml	30	17.95	17.95	4.44	9
Balance Me	Balance Me Congested Skin Serum 15ml	15	36.90	18.45	4.73	44
Benton	Benton Cacao Moist and Mild Serum	30	18.45	18.45	4.50	2
CeraVe	CeraVe Hyaluronic Acid Serum 30ml	30	19.45	19.45	4.56	16
Uriage	Uriage Hyséac New Skin Serum 40ml	40	14.96	19.95	no rating	no review
Versed	Versed Just Breathe Clarifying Serum 30ml	30	20.45	20.45	no rating	no review
The Ordinary	The Ordinary Ethylated Ascorbic Acid 15% Solution	30	20.45	20.45	3.5	6
Spa Magik	Spa Magik Organiks Sleep Therapy 6-Oil Super Serum	50	12.27	20.45	no rating	no review
Spa Magik	Spa Magik Organiks Wrinkle Therapy Omega-Youth Smoothing Serum	50	12.27	20.45	no rating	no review
APIVITA	APIVITA Aqua Beelicious Booster 30ml	30	21.45	21.45	no rating	no review
TRUE	TRUE Skincare Radiance Renewal 10% Stabilised Vitamin C Serum 30ml	30	21.95	21.95	5	1
The Ordinary	The Ordinary Anti-Ageing Hydration Duo 2 x 30ml	60	10.98	21.95	5	9
La Roche-Posay	La Roche-Posay Rosaliac AR Intense Serum 40ml	40	16.84	22.45	4	36
Bioderma	Bioderma Hydrabio Moisturising Serum Dehydrated Skin 40ml	40	16.84	22.45	4.5	4
Indeed	Indeed Labs Eysilix Serum 2 15ml	15	45.90	22.95	5.00	1
L'Oréal	L'Oréal Paris Revitalift Filler + Hyaluronic Acid Replumping Serum 16ml	16	43.03	22.95	4.5	2
Sukin	Sukin Hydration Biomarine Facial Serum 30ml	30	22.95	22.95	no rating	no review
Versed	Versed Press Restart Gentle Retinol Serum 30ml	30	22.95	22.95	no rating	no review
Sanctuary Spa	Sanctuary Spa Hyaluronic Wonder Oil Serum 30ml	30	22.95	22.95	4.76	58
L'Oréal	L'Oréal Paris Age Perfect Nutrition Intense Supreme Repairing Serum	30	22.95	22.95	5	2
Sukin	Sukin Purely Ageless Firming Serum 30ml	30	22.95	22.95	4	1
NIP+FAB	NIP+FAB Dragons Blood Fix Serum 50ml	50	13.77	22.95	4.72	18
NIP+FAB	NIP+FAB Salicylic Fix Serum Extreme 2% 50ml	50	13.77	22.95	4.50	8
NIP+FAB	NIP+FAB Vitamin C Fix Serum 50ml	50	13.77	22.95	5	2
The Jojoba Compan	The Jojoba Company Blemish Control Serum 50ml	50	13.77	22.95	5	1
Rodial	Rodial Pink Diamond Instant Lift Serum 5ml	5	143.70	23.95	no rating	no review
Avène	Avène Hydrance Intense Rehydrating Serum for Dehydrated Skin 30ml	30	23.95	23.95	4.61	31
Indeed	Indeed Labs Hydraluron Moisture Boosting Facial Serum 30ml	30	23.95	23.95	4.58	12
NIOD	NIOD Modulating Glucosides Serum 30ml	30	23.95	23.95	4.57	7
Green People	Green People Neutral/Scent Free Hydrating Calming Serum 50ml	50	14.37	23.95	no rating	no review
Green People	Green People Hydrating Firming Serum (50ml)	50	14.37	23.95	4.50	2
Green People	Green People Organic Homme 7 Active Fix Repair Serum (50ml)	50	14.37	23.95	3.00	1
Benton	Benton Snail Bee Ultimate Serum	35	20.96	24.45	4.25	4
La Roche-Posay	La Roche-Posay Hydraphase Intense Serum (30ml)	30	24.95	24.95	4.54	13
MISSHA	MISSHA Super Aqua Ultra Waterful Intensive Serum 40ml	40	18.71	24.95	no rating	no review
Dear, Klairs	Dear, Klairs Rich Moist Soothing Serum 80ml	80	9.36	24.95	5.00	5
NIP+FAB	NIP+FAB Dragon's Blood Fix Extreme Serum	50	15.57	25.95	4.00	2
Bioderma	Bioderma Pigmentbio Brightening Vitamin C Face Serum Anti-Dark Spot 15ml	15	52.90	26.45	3.67	6
Benton	Benton Snail Bee High Content Essence 60ml	60	13.23	26.45	4.83	6
Dr. Hauschka	Dr. Hauschka Night Serum 20ml	20	40.43	26.95	no rating	no review
The Ordinary	The Ordinary 'Buffet' Multi-Technology Peptide Serum Exclusive Duo	60	13.48	26.95	5.00	1
LIXIRSKIN	LIXIRSKIN Night Switch Essential Lipids 15ml	15	54.90	27.45	3.00	1
NIOD	NIOD Survival 20 Serum 30ml	30	27.45	27.45	5.00	3
Avène	Avène Les Essentiels Radiance Serum for Dull, Sensitive Skin 30ml	30	27.45	27.45	5.00	2
The Ordinary	The Ordinary Buffet Supersize Serum 60ml	60	13.98	27.95	4.77	13
SVR	SVR Laboratoires Sebiaclear Serum for Mature Acne 30ml	30	28.45	28.45	no rating	no review
L'Oréal	L'Oréal Paris 1.5% Hyaluronic Acid Revitalift Filler Serum 30ml	30	28.45	28.45	4.58	19
Lumene	Lumene Nordic Hydra [Lähde] Arctic Dew Quenching Aqua Serum 30ml	30	28.45	28.45	4.43	7
L'Oréal	L'Oreal Paris Dermo Expertise Revitalift Laser Renew Anti-ageing Triple Action Super Serum (30r	30	28.45	28.45	4.60	5
NIOD	NIOD Survival 30 Serum 30ml	30	28.45	28.45	5.00	4
VICHY	VICHY Aqualia Thermal Rehydrating Serum 30ml	30	28.45	28.45	5.00	2
Indeed	Indeed Labs Snoxin Serum 2 30ml	30	28.45	28.45	5.00	1
VICHY	VICHY Minéral 89 Hyaluronic Acid Hydration Booster 50ml	50	17.07	28.45	4.62	130
Benton	Benton Fermentation Essence 100ml	100	8.54	28.45	4.00	1
AROMATICA	AROMATICA Rose Absolute First Serum 130ml	130	6.57	28.45	no rating	no review
Fresh	Fresh Vitamin Nectar Antioxidant Face Serum 15ml	15	58.90	29.45	5.00	1
Pixi	PIXI Vitamin-C Serum 30ml	30	29.45	29.45	4.50	12
Pixi	PIXI Overnight Glow Serum	30	29.45	29.45	4.64	11
Pixi	PIXI Hydrating Milky Serum 30ml	30	29.45	29.45	4.44	9
Pixi	Pixi Clarity Concentrate 30ml	30	29.45	29.45	4.50	8
Pixi	PIXI Glow Tonic Serum 30ml	30	29.45	29.45	4.40	5
Pixi	PIXI Collagen and Retinol Serum 30ml	30	29.45	29.45	4.25	4
Aurelia	Aurelia London The Probiotic Concentrate 10ml	10	91.35	30.45	4.29	7
Lumene	Lumene Invisible Illumination Instant Glow Beauty Serum 30ml	30	30.95	30.95	4.55	31
Avène	Avène A-Oxitive Antioxidant Defence Serum for First Signs of Ageing 30ml	30	31.45	31.45	4.00	3

Rituals	Rituals The Ritual of Namaste Intense Hydrating Serum	30	31.95	31.95	no rating	no review
Aveda	Aveda Hand Relief Night Renewal Serum 30ml	30	31.95	31.95	5.00	2
Medik8	Medik8 Retinol 3TR Serum 15ml	15	65.90	32.95	4.54	13
Lierac	Lierac Magnificence Red Serum Intensive Revitalising 30ml	30	32.95	32.95	no rating	no review
Caudalie	Caudalie Vinosource SOS Thirst Quenching Serum 30ml	30	32.95	32.95	4.74	65
The Ordinary	The Ordinary "Buffet" + Copper Peptides 1%	30	32.95	32.95	4.36	11
skinChemists	skinChemists Oui Essential Hydrating Facial Serum 30ml	30	32.95	32.95	4.67	6
Caudalie	Caudalie Vinopure Blemish Control Salicylic Serum 30ml	30	32.95	32.95	5	2
Caudalie	Caudalie Vinosource-Hydra SOS Thirst-Quenching Serum 30ml	30	32.95	32.95	5	2
VICHY	VICHY Minéral 89 Probiotic Fractions Recovery Serum with 4% Niacinamide 30ml	30	32.95	32.95	3	2
NUXE	NUXE Crème Fraîche de Beauté Serum 30ml	30	32.95	32.95	4	1
iluminage	iluminage Youth Activator Contouring Serum 50ml	50	19.77	32.95	no rating	no review
Trilogy	Trilogy Rosapene Radiance Serum 30ml	30	33.45	33.45	3	2
Trilogy	Trilogy Very Gentle Calming Serum 30ml	30	33.45	33.45	4	1
Balance Me	Balance Me Tri-Molecular Hyaluronic Serum 30ml	30	33.95	33.95	no rating	no review
Lumene	Lumene Nordic C [Valo] Glow Boost Essence 30ml	30	33.95	33.95	4.74	50
Antipodes	Antipodes Hosanna H2O Intensive Skin-Plumping Facial Serum 30ml	30	33.95	33.95	4.5	6
The Organic	The Organic Pharmacy Hyaluronic Acid Serum 30ml	30	33.95	33.95	4.5	4
Rituals	Rituals The Ritual of Namaste Anti-Aging Serum	30	33.95	33.95	3	1
NIP+FAB	NIP+FAB Retinol Fix Serum Extreme 50ml	50	20.37	33.95	5.00	3
Olay	Olay Regenerist Hydrating Face Serum with Niacinamide and Peptides 50ml	50	20.37	33.95	5	1
VICHY	VICHY Minéral 89 Hyaluronic Acid Hydration Booster 75ml	75	13.58	33.95	4.71	41
PRAI	PRAI AGELESS Throat & Decolletage Serum 120ml	120	8.49	33.95	4.92	12
Lancôme	Lancôme Advanced Génifique Youth Activating Serum 20ml	20	53.18	35.45	4.69	no review
PAYOT	PAYOT Elixir Refiner Face Serum 30ml	30	35.45	35.45	no rating	no review
COSRX AC	COSRX AC Collection Blemish Spot Clearing Serum 40ml	40	26.59	35.45	5.00	1
freezeframe	freezeframe Instant V-Lift Serum 30ml	30	35.95	35.95	no rating	no review
Trilogy	Trilogy Nutrient Plus Firming Serum 30ml	30	35.95	35.95	4.60	5
Rodial	Rodial Rose Gold Deluxe Serum 5ml	5	218.70	36.45	no rating	no review
Shiseido	Shiseido Ultimune Power Infusing Concentrate 15ml	15	72.90	36.45	4.85	no review
ilapothecary	ilapothecary Reset Vitamin A Face Serum 20ml	20	54.68	36.45	5.00	1
Too Faced	Too Faced Hangover Good in Bed Ultra-Hydrating Replenishing Serum	29	37.71	36.45	5.00	2
Avène	Avène Physiolift Smoothing and Plumping Serum for Ageing Skin 30ml	30	36.45	36.45	no rating	no review
NEOSTRATA	NEOSTRATA Restore Bionic Face Serum 30ml	30	36.45	36.45	no rating	no review
Balance Me	Balance Me Vitamin C Repair Serum 30ml	30	36.45	36.45	4.88	8
VICHY	VICHY Liftactiv Serum 10 Supreme 30ml	30	36.45	36.45	4.83	6
Balance Me	Balance Me Bakuchiol Smoothing Serum 30ml	30	36.45	36.45	5.00	1
Rituals	Rituals The Ritual of Namaste Active Firming Serum	30	36.45	36.45	5.00	1
The Organic	The Organic Pharmacy Retinol Night Serum 30ml	30	36.45	36.45	5.00	1
FIT	FIT Flaw-Less Blemish Repair Serum 100ml	100	10.94	36.45	no rating	no review
Medik8	Medik8 Retinol 3TR 15ml	15	74.90	37.45	4.63	8
Lumene	Lumene Arctic Hydra Care [Arktis] Moisture & Relief Rich Oleo-Serum 30ml	30	37.45	37.45	no rating	no review
Eucerin	Eucerin® Anti-Age Hyaluron-Filler Concentrate (6 x 5ml)	30	37.45	37.45	4.00	2
Lierac	Lierac Hydragenist Moisturising Serum 30ml	30	37.45	37.45	5.00	1
Mavala	Mavala Aqua Plus Multi-Moisturising Intensive Serum 30ml	30	38.45	38.45	5	2
VICHY	VICHY Neovadiol Compensating Complex Concentrate 30ml	30	38.45	38.45	5	1
Dr.Jart+	Dr.Jart+ Ceramidin Serum 40ml	40	28.84	38.45	4.5	14
FIT	FIT Moisturising Ultra Serum 30ml	30	39.95	39.95	no rating	no review
Polaar	Polaar Anti-Imperfection Solution 30ml	30	39.95	39.95	no rating	no review
Medik8	Medik8 C-Tetra Serum 30ml	30	39.95	39.95	4.45	62
Tan-Luxe	Tan-Luxe Super Glow Hyaluronic Self-Tan Serum 30ml	30	39.95	39.95	4.14	44
Antipodes	Antipodes Worship Skin Defence Antioxidant Serum 30ml	30	39.95	39.95	4.75	4
Medik8	Medik8 Sleep Glycolic Serum 30ml	30	39.95	39.95	4.75	4
Antipodes	Antipodes Blessing Anti-Pollution Light Face Serum 30ml	30	39.95	39.95	4.5	2
Neal's Yard Remedi	Neal's Yard Remedies Beauty Sleep Concentrate 30ml	30	39.95	39.95	5	2
Antipodes	Antipodes Glow Ritual Vitamin C Serum with Plant Hyaluronic Acid 30ml	30	39.95	39.95	5	1
Neal's Yard Remedi	Neal's Yard Remedies Sensitive Soothing Daily Serum 30ml	30	39.95	39.95	5	1
Polaar	Polaar White Siberian Serum 30ml	30	40.95	40.95	no rating	no review
SVR	SVR Clairial Hyperpigmentation Serum - 30ml	30	40.95	40.95	no rating	no review
NUXE	NUXE Chia Seeds Essential Antioxidant Serum 30ml	30	40.95	40.95	4	1
Holika Holika	Holika Holika Gold Kiwi Vita C+ Brightening Serum 45ml	45	27.30	40.95	no rating	no review
Mavala	Mavala Skin Vitality Vitalizing Healthy Glow Serum 30ml	30	41.95	41.95	no rating	no review
this works	this works Morning Expert Hyaluronic Serum 30ml	30	41.95	41.95	4.9	10
Löwengrip	Löwengrip The Serum Facial Serum 30ml	30	41.95	41.95	4.5	2
NIOD	NIOD Lip Bio-Lipid Concentrate 15ml	15	85.90	42.95	3.44	18
NIOD	NIOD Copper Amino Isolate Serum 2:1 15ml	15	85.90	42.95	4.50	2
Eucerin	Eucerin A/A Hyaluron Filler Serum 30ml	30	42.95	42.95	no rating	no review
philosophy	philosophy Renewed Hope in a Jar Serum 30ml	30	42.95	42.95	no rating	no review
PRAI	PRAI PLATINUM Night Caviar Firm & Lift Serum 30ml	30	42.95	42.95	no rating	no review
La Roche-Posay	La Roche-Posay Hyalu B5 Hyaluronic Acid Serum 30ml	30	42.95	42.95	4.69	55
La Roche-Posay	La Roche-Posay Pure Vitamin C10 Serum 30ml	30	42.95	42.95	3.96	50
Dr.Jart+	Dr.Jart+ Cicapair Tiger Grass Re.pair Serum 30ml	30	42.95	42.95	4.88	17
Eucerin	Eucerin Hyaluron Filler Night Peeling and Serum 30ml	30	42.95	42.95	4.50	4
Five Dot Botanics	Five Dot Botanics Deep Feed Green Coffee and Cacay Nourishing Facial Serum 30ml	30	42.95	42.95	5.00	4
PRAI	PRAI 24K GOLD Concentrate Retinol+ 30ml	30	42.95	42.95	4.25	4
Huxley	Huxley Brightly Ever After Essence 30ml	30	42.95	42.95	5.00	2
Crystal Clear	Crystal Clear No Shine Serum 50ml	50	25.77	42.95	5.00	2
BABOR	BABOR Doctor Refine Cellular Glow Booster Bi-Phase 14 x 1ml	14	93.11	43.45	no rating	no review
La Roche-Posay	La Roche-Posay Pure Vitamin C10 Anti-Ageing Serum 30ml	30	43.95	43.95	no rating	no review
Murad	Murad Retinol Youth Renewal Serum	30	44.45	44.45	no rating	no review

The Organic	The Organic Pharmacy Skin Rescue Serum 30ml	30	44.45	44.45	no rating	no review
The Organic	The Organic Pharmacy Virgin Cold Pressed Rosehip Serum 30ml	30	44.45	44.45	no rating	no review
Pestle & Mortar	Pestle & Mortar Pure Hyaluronic Serum 30ml	30	44.45	44.45	4.81	26
Medik8	Medik8 Crystal Retinal 1 Serum 30ml	30	44.45	44.45	4.70	23
Pai	Pai Skincare All Becomes Clear Copaiba and Zinc Blemish Serum 30ml	30	44.45	44.45	4.67	3
Green People	Green People Age Defy+ Hydrate & Renew Face and Neck Serum (30ml)	30	44.45	44.45	4.00	1
ilapothecary	ilapothecary Save Face Serum 50ml	50	26.67	44.45	no rating	no review
ilapothecary	ilapothecary Stubble Trouble Face Serum 50ml	50	26.67	44.45	no rating	no review
Acorelle	Acorelle Hair Regrowth Inhibitor Serum 50ml	50	26.67	44.45	4.00	1
Dermalogica	Dermalogica Redness Relief Essence 150ml	150	8.89	44.45	3.00	2
Comfort	Comfort Zone Hydramemory Essence 100ml	100	13.49	44.95	no rating	no review
Erborian	Erborian Bamboo Super Serum - 30ml	30	45.45	45.45	no rating	no review
Medik8	Medik8 Hydr8 B5 Serum 30ml	30	45.45	45.45	4.77	26
REN Clean	REN Clean Skincare Radiance Perfection Serum 30ml	30	45.45	45.45	4.33	21
Clinique	Clinique Pore Refining Solutions Correcting Serum	30	45.45	45.45	4.8	5
Antipodes	Antipodes Joyous Protein-Rich Night Replenish Facial Serum 30ml	30	45.45	45.45	4.67	3
VICHY	VICHY Liftactiv Serum 10 Supreme 50ml	50	27.27	45.45	4.5	4
Liz Earle	Liz Earle Superskin Face Serum 30ml Pump	30	45.95	45.95	4.92	13
Weleda	Weleda Evening Primrose Concentrate 30ml	30	46.45	46.45	no rating	no review
Weleda	Weleda Pomegranate Firming Face Serum (30ml)	30	46.45	46.45	no rating	no review
Kiehl's	Kiehl's Midnight Recovery Concentrate 30ml	30	46.45	46.45	4.85	26
The Jojoba Compan	The Jojoba Company CoQ10 Antioxidant Serum	30	46.95	46.95	5	1
Talika	Talika Skintelligence Anti-Age Regenerating Serum 30ml	30	47.45	47.45	no rating	no review
Löwengrip	Löwengrip Instant Glow Serum Drops 30ml	30	47.95	47.95	no rating	no review
Anthony	Anthony Vitamin C Facial Serum 30ml	30	47.95	47.95	5	4
Kiehl's	Kiehl's Vital Skin-Strengthening Super Serum 30ml	30	47.95	47.95	5	1
Neal's Yard Remedi	Neal's Yard Remedies Rejuvenating Frankincense Facial Serum 30ml	30	48.45	48.45	no rating	no review
Elizabeth Arden	Elizabeth Arden Ceramide Capsules Advanced (30 Capsules)	14	104.89	48.95	4.11	9
Ecooking	Ecooking Acne Serum 20ml	20	73.43	48.95	no rating	no review
Ecooking	Ecooking Moisturising Serum 20ml	20	73.43	48.95	3.86	7
Ecooking	Ecooking Vitamin E Serum 20ml	20	73.43	48.95	5	1
Ecooking	Ecooking Vitamin A Serum in Capsules (Pack of 60)	28	52.45	48.95	5	7
Ecooking	Ecooking Firming Serum in Capsules (Pack of 60)	28	52.45	48.95	5	3
Origins	Origins Plantscription Multi-Powered Youth Serum 30ml	30	48.95	48.95	no rating	no review
SVR	SVR Densitium Firming Double Serum - 30ml	30	48.95	48.95	5	1
Dr. Brandt	Dr. Brandt Bright Biotic Dark Spot Minimizing Serum 50ml	50	29.37	48.95	4	1
BABOR	BABOR Doctor Lifting Cellular Vitamin C Booster Concentrate 20ml	20	74.18	49.45	no rating	no review
Lierac	Lierac Mésolift Ultra Vitamin-Enriched Anti-Fatigue Correction Serum	30	49.95	49.95	no rating	no review
Pai	Pai Skincare Back to Life Jojoba and Hyaluronic Acid Hydration Serum 30ml	30	49.95	49.95	4.64	11
Elizabeth Arden	Elizabeth Arden Retinol Ceramide Capsules Line Erasing Night Serum - 30 Pieces (Sleeved Versio	14	109.18	50.95	3.85	13
Elizabeth Arden	Elizabeth Arden Vitamin C Ceramide Capsules Radiance Renewal Serum 30pc	14	109.18	50.95	4	6
Medik8	Medik8 Intelligent Retinol 10TR 15ml	15	101.90	50.95	5	4
NEOM	NEOM Ultimate Calm Face Serum 28ml	28	54.59	50.95	no rating	no review
NEOM	NEOM Great Day Glow Face Serum 28ml	28	54.59	50.95	5	1
ARK	ARK Skincare Firming Serum 30ml	30	50.95	50.95	no rating	no review
ARK	ARK Skincare Hydrating Serum 30ml	30	50.95	50.95	no rating	no review
Dr. Hauschka	Dr. Hauschka Regenerating Serum 30g	30	50.95	50.95	no rating	no review
Elemental Herbolog	Elemental Herbology Bio-Cellular Matrix Serum	30	50.95	50.95	no rating	no review
Lancaster	Lancaster 365 Skin Repair Serum Youth Renewal 30ml	30	50.95	50.95	no rating	no review
Tria Age	Tria Age Defying Skincare Finishing Serum	30	50.95	50.95	no rating	no review
Antipodes	Antipodes Apostle Skin-Brightening Serum 30ml	30	50.95	50.95	4.55	11
Aurelia	Aurelia London Revitalise & Glow Serum 30ml	30	50.95	50.95	4.44	9
REN Clean	REN Clean Skincare Evercalm Redness Relief Serum 30ml	30	50.95	50.95	5	9
Medik8	Medik8 Bakuchiol Peptides 30ml	30	50.95	50.95	4	4
ARK	ARK Skincare De-Stress Serum 30ml	30	50.95	50.95	5	1
Ila-Spa	Ila-Spa Face Serum for Renewed Recovery 30ml	30	50.95	50.95	5	1
Polaar	Polaar Eternal Snow Serum 30ml	30	50.95	50.95	3	1
The Organic	The Organic Pharmacy Stabilised Vitamin C Serum 30ml	30	50.95	50.95	5	1
Origins	Origins Original Skin Renewal Serum with Willowherb (50ml)	50	30.57	50.95	4.5	2
Erborian	Erborian Red Pepper Super Serum - 30ml	30	52.45	52.45	no rating	no review
Erborian	Erborian Yuza Super Serum - 30ml	30	52.45	52.45	no rating	no review
Elemental Herbolog	Elemental Herbology Cell Nourish Radiance and Vitality Facial Serum	30	52.45	52.45	4.5	2
NUXE	NUXE Nuxuriance Ultra Serum	30	52.95	52.95	5	2
NEOSTRATA	NEOSTRATA Restore Redness Neutralising Serum 29g	29	55.29	53.45	no rating	no review
Aveda	Aveda Tulasāra™ Bright Concentrate 30ml	30	53.45	53.45	no rating	no review
Aveda	Aveda Tulasāra™ Calm Concentrate 30ml	30	53.45	53.45	5	2
Aesop	Aesop Lightweight Facial Hydrating Serum 100ml	100	16.04	53.45	4.57	7
Biossance	Biossance Squalane and Lactic Acid Resurfacing Serum 30ml	30	54.45	54.45	no rating	no review
DECLÉOR	DECLÉOR Antidote Serum 30ml	30	54.45	54.45	4.33	6
AromaWorks	AromaWorks Absolute Face Serum 30ml	30	54.45	54.45	5	4
GLAMGLOW	GLAMGLOW Youth Potion Rejuvenate Serum 30ml/1oz	30	54.45	54.45	5	2
NARS	NARS Cosmetics Optimal Brightening Concentrate	30	54.95	54.95	5	2
Ecooking	Ecooking Super Serum 20ml	20	83.18	55.45	5	3
Gatineau	Gatineau Perfection Ultime Skin Perfecting Cream-Serum 30ml	30	55.45	55.45	no rating	no review
Darphin	Darphin Hydraskin Serum 30ml	30	55.45	55.45	4	4
FOREO	FOREO SERUM SERUM SERUM Boosting and Firming Serum 30ml	30	55.45	55.45	5	3
Pai	Pai Skincare Instant Kalmer Sea Aster and Schisandra Ceramide Serum 30ml	30	55.45	55.45	4	3
Biossance	Biossance Squalane and Vitamin C Dark Spot Serum 30ml	30	55.45	55.45	5	1
COOLA	COOLA Sunless Tan Face Serum 40ml	40	41.59	55.45	no rating	no review
Anne Semonin	Anne Semonin Glow Instant Radiance Essence 50ml	50	33.27	55.45	no rating	no review

AHAVA	AHAVA Exclusive Activating Smoothing Essence 100ml	100	16.64	55.45	5	1
Comfort	Comfort Zone Sublime Skin Essence 100ml	100	16.79	55.95	no rating	no review
Perricone MD	Perricone MD Vitamin C Ester Brightening Serum	30	56.45	56.45	no rating	no review
DECLÉOR	DECLÉOR Aromessence Rose D'Orient Serum (15ml)	15	113.90	56.95	4.71	7
NuFACE	NuFACE FIX Line Smoothing Serum 15ml	15	113.90	56.95	4.33	3
PRAI	PRAI AGELESS Throat Ionic Serum 30ml	30	56.95	56.95	no rating	no review
REN Clean	REN Clean Skincare Perfect Canvas Serum 30ml	30	56.95	56.95	5	5
Filorga	Filorga Hydra-Hyal Serum 30ml	30	56.95	56.95	5	2
Lab Series	Lab Series Skincare for Men Future Rescue Repair Serum (50ml)	50	34.17	56.95	no rating	no review
Origins	Origins Make A Difference Plus+ Rejuvenating Serum	50	34.17	56.95	5	1
Jack Black	Jack Black Protein Booster Skin Serum (60ml)	60	28.48	56.95	no rating	no review
Dr. Brandt	Dr. Brandt Dark Spots No More Triple Acid Spot Minimising Concentrate 15ml	15	115.90	57.95	no rating	no review
DECLÉOR	DECLÉOR Neroli Bigarade Aromessence Hydrating Serum 15ml	15	117.90	58.95	4.82	33
Jurlique	Jurlique Moisture Plus Rare Rose Serum 30ml	30	58.95	58.95	no rating	no review
Institut Esthederm	Institut Esthederm Intensive Hyaluronic Acid Serum 30ml	30	58.95	58.95	5	2
bareMinerals	bareMinerals Ageless Retinol Night Concentrate 30ml	30	58.95	58.95	4	1
Fresh	Fresh Rose Deep Hydration Oil-Infused Serum 100ml	100	17.69	58.95	5	1
Elemis	Elemis Pro-Collagen Super Serum Elixir 15ml	15	119.90	59.95	4.57	28
AHAVA	AHAVA Age Control Brightening and Renewal Serum 30ml	30	59.95	59.95	no rating	no review
Elemis	Elemis Peptide4 Antioxidant Hydra-Serum 30ml	30	59.95	59.95	3	2
AHAVA	AHAVA Dead Sea Osmoter Concentrate 30ml	30	59.95	59.95	4	1
ESPA	ESPA Repair and Restore Intensive Serum 25ml	25	73.74	61.45	no rating	no review
Emma Hardie	Emma Hardie Vitamin C Intense Daily Serum 30ml	30	61.45	61.45	5.00	1
Gatineau	Gatineau Aquamemory Moisture Replenish Concentrate (30ml)	30	61.45	61.45	5	1
Kiehl's	Kiehl's Powerful-Strength Line-Reducing Concentrate 50ml	50	36.87	61.45	5.00	3
DECLÉOR	DECLÉOR Aromessence Green Mandarin Essential Oil Serum 15ml	15	124.90	62.45	4.90	21
Institut Esthederm	Institut Esthederm Intensive Retinol Face Serum 15ml	15	124.90	62.45	5.00	2
Clinique	Clinique Smart Clinical Repair Wrinkle Correcting Serum 30ml	30	62.45	62.45	no rating	no review
DERMAdoctor	DERMAdoctor Wrinkle Revenge Ultimate Hyaluronic Serum	30	62.45	62.45	no rating	no review
Neal's Yard Remedi	Neal's Yard Remedies Sensitive Restore + Smooth Serum 30ml	30	62.45	62.45	no rating	no review
PAYOT	PAYOT Elixir Lift Face Serum 30ml	30	62.45	62.45	no rating	no review
Medik8	Medik8 Hydr8 B5 Intense 30ml	30	62.45	62.45	4.69	13
FARMACY	FARMACY Honeymoon Glow 30ml	30	62.45	62.45	5.00	7
Anthony	Anthony Anti-Wrinkle Glygolic Peptide Serum 30ml	30	62.45	62.45	5.00	4
ESPA	ESPA Optimal Skin Pro-Serum 30ml	30	62.45	62.45	4.33	3
philosophy	philosophy Time in a Bottle 100% Face Serum 40ml	40	46.84	62.45	5.00	2
Aesop	Aesop Parsley Seed Anti Oxidant Serum 100ml	100	18.74	62.45	4.80	5
Peter Thomas	Peter Thomas Roth Retinol Fusion PM 30ml	30	62.95	62.95	3.20	5
Comfort	Comfort Zone Remedy Serum 30ml	30	63.45	63.45	no rating	no review
Sarah Chapman	Sarah Chapman Skinesis Age Repair Serum (30ml)	30	63.45	63.45	4.67	6
Peter Thomas	Peter Thomas Roth Water Drench Hyaluronic Cloud Serum 1oz	30	63.45	63.45	5.00	1
Dermalogica	Dermalogica Ultra Calming Serum Concentrate	40	47.59	63.45	4.29	7
Darphin	Darphin Lumière Essentielle Serum 30ml	30	65.95	65.95	5.00	2
Dermalogica	Dermalogica AGE Bright Clearing Serum 30ml	30	66.45	66.45	3.83	6
Institut Esthederm	Institut Esthederm Intensive Face Peeling Serum 30ml	30	66.95	66.95	no rating	no review
Swiss Clinic	Swiss Clinic Rejuvenating Serum 30ml	30	66.95	66.95	no rating	no review
Medik8	Medik8 Super C Ferulic 30ml	30	66.95	66.95	4.6	10
Medik8	Medik8 C-Tetra Luxe 30ml	30	66.95	66.95	4.8	5
INIKA	INIKA Phytofuse Renew Resveratrol Serum	30	66.95	66.95	5	2
Jurlique	Jurlique Calendula Redness Rescue Restorative Serum (30ml)	30	66.95	66.95	4.5	2
Swiss Clinic	Swiss Clinic Reviving Face Serum 30ml	30	66.95	66.95	5.00	2
Sepai	Sepai Celebrity Serum 35ml	35	57.81	67.45	no rating	no review
Elizabeth Arden	Elizabeth Arden Skin Illuminating Advanced Brightening Night Capsules (50 Capsules)	12	169.88	67.95	4.67	12
Estée Lauder	Estée Lauder Advanced Night Repair Intense Reset Concentrate 20ml	20	101.93	67.95	4.8	35
Erborian	Erborian Ginseng Super Serum - 30ml	30	67.95	67.95	no rating	no review
Institut Esthederm	Institut Esthederm Restructuring Face Serum 30ml	30	67.95	67.95	no rating	no review
SkinCeuticals	SkinCeuticals Phyto Corrective Hyaluronic Acid Serum Gel 30ml	30	67.95	67.95	no rating	no review
skinChemists	skinChemists London Rose Quartz Mineral Facial Serum 30ml	30	67.95	67.95	no rating	no review
Estée Lauder	Estée Lauder Advanced Night Repair Synchronized Multi-Recovery Complex Serum 30ml	30	67.95	67.95	4.79	160
Shiseido	Shiseido Ultimune Power Infusing Concentrate 30ml	30	67.95	67.95	4.85	47
Lancôme	Lancôme Advanced Génifique Youth Activating Serum 30ml	30	67.95	67.95	4.69	29
NUXE	NUXE Super Serum 30ml	30	67.95	67.95	5	9
Kora	Kora Organics Noni Bright Vitamin C Serum 30ml	30	67.95	67.95	4.17	6
Kiehl's	Kiehl's Vital Skin-Strengthening Super Serum 50ml	50	40.77	67.95	5	no review
Lancaster	Lancaster 365 Skin Repair Serum Youth Renewal 50ml	50	40.77	67.95	no rating	no review
Lancaster	Lancaster 365 Skin Repair Youth Renewal Serum 50 ml	50	40.77	67.95	no rating	no review
Dynamic	Dynamic Resurfacing Skin Smoothing Essence	100	20.39	67.95	5	1
Eve Rebirth	Eve Rebirth Instant Hyalu-Snake Serum	15	137.90	68.95	no rating	no review
Dermalogica	Dermalogica Overnight Repair Serum 15ml	15	137.90	68.95	5	8
Lancôme	Lancôme Advanced Genifique Sensitive Serum 20ml	20	103.43	68.95	no rating	no review
Jurlique	Jurlique Purely White Skin Brightening Essence 30ml	30	68.95	68.95	no rating	no review
Filorga	Filorga NCEF-Shot Supreme Polyrevitalising Concentrate 15ml	15	140.90	70.45	5	1
Filorga	Filorga Skin-Unify Intensive Illuminating Even Skin Tone Serum 30ml	30	70.45	70.45	no rating	no review
Filorga	Filorga Time-Filler Intensive Wrinkle Multi-Correction Serum 30ml	30	70.45	70.45	no rating	no review
Filorga	Filorga C Recover (1oz)	30	70.45	70.45	5	11
Filorga	Filorga Time-Zero Serum 30ml	30	70.45	70.45	4.8	5
StriVectin	StriVectin Super-C Retinol Brighten and Correct Vitamin C Serum 30ml	30	70.45	70.45	5	2
Lancôme	Lancôme Visionnaire Skin Solutions 15% Vitamin C 20ml	20	107.18	71.45	5	1
AHAVA	AHAVA Dead Sea Crystal Osmoter X6 Facial Serum 30ml	30	71.45	71.45	no rating	no review

Institut Esthederm	Institut Esthederm Intensive Vitamin E Antioxidant Face Serum 30ml	30	71.45	71.45	5	1
Lancôme	Lancôme Visionnaire Skin Solutions 0.2% Retinol 30ml	30	71.45	71.45	5	1
Dermalogica	Dermalogica Multivitamin Power Serum (22ml)	22	98.11	71.95	4.75	4
Aurelia	Aurelia London Resurfacing Serum 30ml	30	72.45	72.45	5.00	1
Clinique	Clinique Even Better Clinical Radical Dark Spot Corrector + Interrupter 50ml	50	43.47	72.45	4.19	16
Replenix Retinol	Replenix Retinol 5X Regenerate Dry Anti-Ageing Serum	30	73.45	73.45	no rating	no review
Darphin	Darphin Ideal Resource Perfecting Smoothing Serum (30ml)	30	73.45	73.45	5.00	5
Lancôme	Lancôme Visionnaire Serum Plus 30ml	30	73.45	73.45	5.00	4
Kora	Kora Organics Noni Night AHA Resurfacing Serum 30ml	30	73.45	73.45	5.00	3
NEOSTRATA	NEOSTRATA Enlighten Illuminating Serum 30ml	30	73.45	73.45	5.00	1
Origins	Origins Plantscription Anti-Aging Power Serum 50ml	50	44.07	73.45	5.00	5
Origins	Origins Dr. Andrew Weil for Origins Mega-Mushroom Relief & Resilience Advanced Face Serum	50	44.07	73.45	3.50	2
Aesop	Aesop Parsley Seed Anti-Oxidant Intense Serum 60ml	60	36.73	73.45	no rating	no review
Perricone MD	Perricone MD Face Firming Serum	59	37.86	74.45	5.00	1
OSKIA	OSKIA Super C Smart Nutrient Beauty 60 Capsules	28	80.30	74.95	5.00	6
Jurlique	Jurlique Herbal Recovery Signature Serum 30ml	30	74.95	74.95	no rating	no review
Aurelia	Aurelia London The Probiotic Concentrate 30ml	30	75.45	75.45	5.00	2
Origins	Origins Plantscription Multi-Powered Youth Serum 50ml	50	45.57	75.95	5.00	1
Crystal Clear	Crystal Clear Pharma Grade Hyaluronic Serum 30ml	30	76.45	76.45	5.00	1
SkinCeuticals	SkinCeuticals Hydrating B5 Moisturiser 30ml	30	76.95	76.95	5.00	3
Dr Dennis	Dr Dennis Gross Skincare Alpha Beta Pore Perfecting & Refining Serum 30ml	30	76.95	76.95	4.50	2
Gatineau	Gatineau Collagene Expert Ultimate Smoothing Serum 30ml	30	76.95	76.95	4.00	1
Kate	Kate Somerville Quench Hydrating Face Serum 30ml	30	76.95	76.95	5.00	1
ALGENIST	ALGENIST Power Recharging Night Pressed Serum 60ml	60	38.48	76.95	5.00	1
KORRES	KORRES Golden Krocus Ageless Saffron Elixir Serum 30ml	30	77.45	77.45	4.5	2
Gatineau	Gatineau Age Benefit Integral Regenerating Concentrate 30ml	30	78.45	78.45	no rating	no review
Gatineau	Gatineau Melatogenine Aox Probiotics Youth Activating Beauty Serum 30ml	30	78.45	78.45	no rating	no review
Shiseido	Shiseido Men Ultimune Power Infusing Concentrate 30ml	30	78.45	78.45	no rating	no review
StriVectin	StriVectin Wrinkle Recode™ Line Transforming Melting Serum 30ml	30	78.45	78.45	no rating	no review
Avant	Avant Skincare Hi-Retinol Restoring and Lifting Serum 30ml	30	78.95	78.95	no rating	no review
Murad	Murad Intensive Age-Diffusing Serum 30ml	30	78.95	78.95	no rating	no review
DECLÉOR	DECLÉOR Aromessence Magnolia Youthful Oil Serum 15ml 0.5oz	15	158.90	79.45	5	6
Elemis	Elemis Pro-Collagen Renewal Serum 15ml	15	158.90	79.45	4.5	2
Grown	Grown Alchemist Instant Smoothing Serum 25ml	25	95.34	79.45	no rating	no review
Elizabeth Arden	Elizabeth Arden Ceramide Capsules Advanced (60 Capsules)	28	85.13	79.45	4.89	9
Origins	Origins Three-Part Harmony Serum 30ml	30	79.45	79.45	no rating	no review
Murad	Murad Retinol Youth Renewal Serum 30ml	30	79.45	79.45	4.86	7
Bobbi Brown	Bobbi Brown Extra Repair Serum 30ml	30	79.45	79.45	5	3
Murad	Murad Hydro-Dynamic Quenching Essence 30ml	30	79.45	79.45	5	2
OSKIA	OSKIA Retinoid Sleep Serum Level 1 30ml	30	79.45	79.45	5	1
Kiehl's	Kiehl's Powerful-Strength Line-Reducing Concentrate 75ml	75	31.78	79.45	5.00	no review
Biologi	Biologi Bd Luminosity Face Serum 30ml	30	80.45	80.45	no rating	no review
Allies of Skin	Allies of Skin Multi Hyaluronic Antioxidant Hydration Serum 30ml	30	81.45	81.45	no rating	no review
Comfort	Comfort Zone Sublime Skin Serum 30ml	30	81.45	81.45	no rating	no review
Sepai	Sepai Counter Clockwise Serum 15ml	15	163.90	81.95	no rating	no review
Estée Lauder	Estée Lauder Advanced Night Repair Synchronized Multi-Recovery Complex Serum 50ml	50	49.17	81.95	4.79	no review
Sepai	Sepai Flawless Dark Spots Serum 12ml	12	207.38	82.95	no rating	no review
APIVITA	APIVITA Queen Bee Holistic Age Defense Serum 30ml	30	82.95	82.95	no rating	no review
Clinique	Clinique Smart Clinical Repair Wrinkle Correcting Serum 50ml	50	50.70	84.50	no rating	no review
Elizabeth Arden	Elizabeth Arden Retinol Ceramide Capsules Line Erasing Night Serum - 60 Pieces (Sleeved Versio	28	91.02	84.95	4.71	17
Elizabeth Arden	Elizabeth Arden Vitamin C Ceramide Capsules Radiance Renewal Serum 60pc	28	91.02	84.95	5	3
Rodial	Rodial Snake Serum O2 30ml	30	84.95	84.95	no rating	no review
Eve Lom	Eve Lom Intense Hydration Serum 1oz	30	84.95	84.95	3.33	3
Neal's Yard Remedi	Neal's Yard Remedies Frankincense Intense™ Age-Defying Serum 30ml	30	84.95	84.95	3.67	3
Dr Dennis	Dr Dennis Gross Skincare B3Adaptive Superfoods Stress Rescue Super Serum 30ml	30	84.95	84.95	4.5	2
OSKIA	OSKIA Retinoid Sleep Serum Level 2 30ml	30	84.95	84.95	4	1
Darphin	Darphin Intral Redness Relief Soothing Serum	50	50.97	84.95	4.78	18
MÁDARA	MÁDARA Infinity Drops Immuno-Serum	30	85.45	85.45	no rating	no review
Thalgo	Thalgo Brightening Correcting Serum	30	85.45	85.45	no rating	no review
Jurlique	Jurlique Herbal Recovery Signature Serum 50ml	50	51.27	85.45	no rating	no review
DERMAdoctor	DERMAdoctor Kakadu C 20% Vitamin C Serum with Ferulic Acid and Vitamin E 30ml	30	85.95	85.95	no rating	no review
EISENBERG	EISENBERG Megalift for Men 30ml	30	87.95	87.95	no rating	no review
EISENBERG	EISENBERG Moisturising Smoothing Serum 30ml	30	87.95	87.95	no rating	no review
Filorga	Filorga NCTF-Intensive 30ml	30	88.45	88.45	5.00	3
Thalgo	Thalgo Wrinkle Lifting Serum	30	88.45	88.45	5.00	1
Dr Dennis	Dr Dennis Gross Skincare C+Collagen Brighten	30	89.45	89.45	4.33	3
ALGENIST	ALGENIST AA Barrier Serum 30ml	30	90.45	90.45	no rating	no review
philosophy	philosophy Brighten My Day Essence 30ml	30	90.45	90.45	no rating	no review
Institut Esthederm	Institut Esthederm Eve Regenerating Face Serum 30ml	30	90.45	90.45	4.70	10
VERSO	VERSO Hydration Serum 30ml	30	90.45	90.45	5.00	1
BABOR	BABOR Doctor Repair Cellular Ultimate ECM Repair Serum 50ml	50	54.27	90.45	no rating	no review
Biologi	Biologi Bm Regenerate Anti-Ageing Serum 30ml	30	91.95	91.95	no rating	no review
Peter Thomas	Peter Thomas Roth Potent-C Power Serum	30	91.95	91.95	4.43	7
ALGENIST	ALGENIST ELEVATE Advanced Retinol Serum 30ml	30	91.95	91.95	4.00	1
Dermalogica	Dermalogica Biolumin C Serum 30ml	40	69.34	92.45	5.00	1
PAYOT	PAYOT Uni Skin Concentré Perles Illuminating Serum 30ml	30	92.95	92.95	no rating	no review
Shiseido	Shiseido Benefiance Wrinkle Smoothing Contour Serum 30ml	30	92.95	92.95	5.00	2
Estée Lauder	Estée Lauder Advanced Night Repair Serum Synchronized Multi-Recovery Complex with Pink Rib	50	55.77	92.95	no rating	no review
Shiseido	Shiseido Ultimune Power Infusing Concentrate 50ml	50	56.37	93.95	4.85	no review
IOMA	IOMA Youth Pearl Essence Anti-Ageing Serum 40ml	40	70.84	94.45	no rating	no review
Darphin	Darphin Exquisage Serum (30ml)	30	94.95	94.95	no rating	no review
Kate	Kate Somerville Wrinkle Warrior 2-in-1 Moisturiser and Serum 50ml	50	56.97	94.95	no rating	no review
Estée Lauder	Estée Lauder Perfectionist [CP+R] Wrinkle Lifting/Firming Serum 50ml	50	56.97	94.95	4.83	23
SkinCeuticals	SkinCeuticals Serum 10 Antioxidant Vitamin C Serum for Sensitive Skin 30ml	30	96.45	96.45	4.55	11
SkinCeuticals	SkinCeuticals Discoloration Defense Corrective Serum 30ml	30	96.45	96.45	3.60	5
ALGENIST	ALGENIST Genius Ultimate Anti-Ageing Vitamin C+ Serum 30ml	30	96.45	96.45	4.00	1
The Organic	The Organic Pharmacy Antioxidant Face Serum 35ml	35	82.67	96.45	no rating	no review
Dr. Brandt	Dr. Brandt C Scription Brightening Serum 30ml	30	97.45	97.45	no rating	no review
Filorga	Filorga Global Repair Intensive Serum 30ml	30	97.45	97.45	no rating	no review
Institut Esthederm	Institut Esthederm Excellage Firming Face Serum 30ml	30	97.45	97.45	no rating	no review

Obagi	Obagi Professional-C Serum 10% 30ml	30	97.45	97.45	3.50	2
Elizabeth Arden	Elizabeth Arden Ceramide Capsules Advanced (90 Capsules)	42	70.32	98.45	4.62	21
Dermalogica	Dermalogica C-12 Pure Bright Serum - PowerBright TRx	50	59.37	98.95	4.00	3
Allies of Skin	Allies of Skin Mandelic Pigmentation Corrector Night Serum 30ml	30	100.95	100.95	no rating	no review
Dermalogica	Dermalogica Powerbright Dark Spot Serum 30ml	30	100.95	100.95	no rating	no review
EISENBERG	EISENBERG Pure White Essential Moisturising Serum	30	100.95	100.95	no rating	no review
Avant	Avant Skincare 8 Hour Anti-Oxidising and Retexturing Hyaluronic Facial Serum 30ml	30	100.95	100.95	4.93	14
Estée Lauder	Estée Lauder Ampoules Advanced Night Repair Serum 30ml	30	100.95	100.95	4.75	4
StriVectin	StriVectin AR™AR Advanced Concentrated Serum (30ml/1oz)	30	100.95	100.95	5.00	1
Perricone MD	Perricone MD High Potency Growth Factor Firming and Lifting Serum 59ml	59	51.58	101.45	no rating	no review
Kiehl's	Kiehl's Powerful-Strength Line-Reducing Concentrate 100ml	100	30.44	101.45	5.00	no review
SkinCeuticals	SkinCeuticals H.A. Intensifier Serum 30ml	30	101.95	101.95	4.64	11
Omorovicza	Omorovicza Instant Perfection Serum (30ml)	30	101.95	101.95	4	6
SkinCeuticals	SkinCeuticals Blemish and Age Defense Corrective Serum 30ml	30	101.95	101.95	4.33	6
Caudalie	Caudalie Premier Cru Serum 30ml	30	101.95	101.95	5.00	3
Omorovicza	Omorovicza Rose Lifting Serum (30ml)	30	101.95	101.95	4.50	2
Elizabeth Arden	Elizabeth Arden Retinol Ceramide Capsules - 90 Capsules	42	72.82	101.95	5	15
SENSORI+	SENSORI+ Clarifying & Strengthening Serum-in-Oil 30ml	30	103.45	103.45	no rating	no review
Avant	Avant Skincare Pink Orchid Subtle Restoring Overnight Serum 30ml	30	104.45	104.45	4.5	8
OSKIA	OSKIA Super 16 Serum (30ml)	30	104.45	104.45	4.75	8
Avant	Avant Skincare Marvellous Nocturnal Resurfacing Hyaluronic Facial Serum 30ml	30	106.45	106.45	no rating	no review
RéVive	RéVive Lip & Perioral Renewal Serum	15	214.90	107.45	5	1
Sarah Chapman	Sarah Chapman Skinesis Age Repair Concentrate (30ml)	30	107.45	107.45	no rating	no review
CULT51	CULT51 Immediate Effects Serum	30	107.45	107.45	5	3
Shiseido	Shiseido Ultimune Power Infusing Concentrate 75ml Refill	75	42.98	107.45	4.85	no review
Kiehl's	Kiehl's Midnight Recovery Concentrate 100ml	100	32.69	108.95	4.85	no review
Thalgo	Thalgo Intensive Redensifying Serum	30	110.45	110.45	no rating	no review
DCL	DCL Hydra Boost Finishing Serum	30	110.95	110.95	no rating	no review
Erno Laszlo	Erno Laszlo Hydra-Therapy Refresh Infusion Serum 1oz	30	110.95	110.95	4.5	2
Chantecaille	Chantecaille Vital Essence 50ml	50	66.57	110.95	4.5	2
BABOR	BABOR Doctor Refine Cellular Ultimate A16 Booster Concentrate 30ml	30	111.95	111.95	no rating	no review
EISENBERG	EISENBERG Comforting Calming Serum 30ml	30	111.95	111.95	no rating	no review
Rodial	Rodial Pink Diamond Instant Lifting Serum 30ml	30	113.45	113.45	no rating	no review
Erno Laszlo	Erno Laszlo AHA Resurfacing Sleep Serum	30	113.45	113.45	5	7
Goldfaden MD	Goldfaden MD Needle-less Line Smoothing Concentrate 30ml	30	113.45	113.45	4.29	7
Decorté	Decorté Lift Dimension Serum	50	68.07	113.45	5	1
Gatineau	Gatineau Age Benefit Regenerating Night Elixir 15ml	15	235.90	117.95	no rating	no review
Avant	Avant Skincare R.N.A Radical Firmness Anti-Ageing Serum 30ml	30	117.95	117.95	5	4
By Terry	By Terry Detoxilyn City Serum	30	118.95	118.95	no rating	no review
Shiseido	Shiseido Ultimune Power Infusing Concentrate 75ml	75	47.58	118.95	4.85	no review
Perricone MD	Perricone MD Essential Fx Acyl-Glutathione: Deep Crease Serum	30	119.45	119.45	no rating	no review
Perricone MD	Perricone MD Cold Plasma Plus Serum 30ml	30	119.45	119.45	5	1
Skin Authority	Skin Authority Wrinkle Reversing Serum	15	245.90	122.95	no rating	no review
Avant	Avant Skincare Age Prestige Antioxidising and Detoxifying Rose Serum 30ml	30	123.45	123.45	no rating	no review
Perricone MD	Perricone MD Cold Plasma Plus+ CBD Advanced Serum Concentrate 30ml	30	123.95	123.95	no rating	no review
Radical Skincare	Radical Skincare Youth Infusion Serum 30ml	30	124.45	124.45	no rating	no review
Romilly Wilde	Romilly Wilde Advanced Supercell Serum	30	124.45	124.45	5	3
VERSO	VERSO Super Facial Serum 30ml	30	124.45	124.45	5	2
Chantecaille	Chantecaille Anti-Pollution Finishing Essence 30ml	30	126.95	126.95	5	1
Avant	Avant Skincare Damascan Rose Petals Revitalising Facial Serum 30ml	30	129.95	129.95	no rating	no review
Elemis	Elemis Pro-Collagen Quartz Lift Serum 30ml	30	129.95	129.95	4.43	7
BIOEFFECT	BIOEFFECT EGF Day Serum 30ml	30	129.95	129.95	4.2	5
Jurlique	Jurlique Nutri-Define Supreme Rejuvenating Serum	30	129.95	129.95	5	1
Darphin	Darphin Predermine Firming Wrinkle Repair Serum 30ml	30	133.45	133.45	5	1
Dr. Brandt	Dr. Brandt Do Not Age Transforming Pearl Serum 40ml	40	100.84	134.45	no rating	no review
Dr. Brandt	Dr. Brandt Do Not Age with Dr. Brandt Transforming Pearl Serum (40ml)	40	100.84	134.45	5	2
Gentlemen's Tonic	Gentlemen's Tonic Advanced Derma Care Brightening Serum 30ml	30	134.95	134.95	no rating	no review
BAKEL	BAKEL Malic Lightening and Renewing Serum (30ml)	30	135.95	135.95	4	1
Eve Lom	Eve Lom White Advanced Brightening Serum (30ml)	30	135.95	135.95	5	1
Clinique	Clinique Smart Clinical Repair Wrinkle Correcting Serum 100ml	100	40.79	135.95	no rating	no review
Dermalogica	Dermalogica Biolumin C Serum 59ml	59	71.67	140.95	5	1
Zirh	Zirh Platinum PM Rescue Night Time Firming Serum 50ml	50	84.87	141.45	no rating	no review
Decorté	Decorté Whitelogist Brightening Correcting Serum with Kojic Acid 40ml	40	106.84	142.45	no rating	no review
Avant	Avant Skincare Sublime Peony and White Caviar Illuminating Pearls Serum 30ml	30	144.95	144.95	no rating	no review
Dermalogica	Dermalogica Smart Response Serum 30ml	30	146.95	146.95	no rating	no review
Dermalogica	Dermalogica Phyto Nature Serum 40ml	40	110.21	146.95	5	1
Lancôme	Lancôme Advanced Génifique Youth Activating Serum 75ml	75	58.78	146.95	4.69	no review
Chantecaille	Chantecaille Blue Light Protection Hyaluronic Serum 30ml	30	152.95	152.95	no rating	no review
Medik8	Medik8 r-Retinoate Day and Night Serum 50ml	50	91.77	152.95	3.5	2
Gentlemen's Tonic	Gentlemen's Tonic Advanced Derma Care Hero Peptide Serum 30ml	30	157.45	157.45	no rating	no review

SkinCeuticals	SkinCeuticals C E Ferulic Antioxidant Vitamin C Serum for Normal/Dry Skin 30ml	30	158.45	158.45	4.63	24
Sarah Chapman	Sarah Chapman Platinum Stem Cell Elixir 30ml	30	166.45	166.45	no rating	no review
Sepai	Sepai Booster+ Recovery Serum 35ml	35	143.53	167.45	no rating	no review
Sepai	Sepai Restart Recovery Serum 35ml	35	143.53	167.45	no rating	no review
Elemis	Elemis Pro-Collagen Overnight Matrix 50ml	50	100.47	167.45	5	12
Zelens	Zelens Z-Melatonin Overnight Serum 30ml	20	279.68	186.45	no rating	no review
Erno Laszlo	Erno Laszlo Timeless Skin Serum (1.7oz)	51	112.62	191.45	no rating	no review
Shiseido	Shiseido Vital Perfection LiftDefine Radiance Serum 80ml	80	73.86	196.95	no rating	no review
Ila-Spa	Ila-Spa Gold Cellular Age-Restore Face Serum 30ml	30	203.45	203.45	no rating	no review
Elizabeth Arden	Elizabeth Arden Prevage Anti-Aging Intensive Repair Daily Serum	30	203.45	203.45	4.73	11
RéVive	RéVive Moisturizing Renewal Serum	30	209.45	209.45	no rating	no review
RéVive	RéVive Moisturising Renewal Hydrogel Targeted 4D Hydration Serum 87g	80	78.54	209.45	no rating	no review
Natura Bissé	Natura Bissé Essential Shock Intense Complex 30ml	30	211.45	211.45	no rating	no review
111SKIN	111SKIN Y Theorem Repair Light Serum NAC Y2 (30ml)	30	214.95	214.95	no rating	no review
Darphin	Darphin Stimulskin Absolute Renewal Serum 30ml	30	214.95	214.95	no rating	no review
Rodial	Rodial Rose Gold Serum 30ml	30	214.95	214.95	no rating	no review
111SKIN	111SKIN Y Theorem Repair Serum NAC Y2 (30ml)	30	214.95	214.95	5	4
Darphin	Darphin Stimulskin Plus Reshaping Divine Serum	30	214.95	214.95	5	1
Chantecaille	Chantecaille Radiance Elixir 30ml	30	223.95	223.95	no rating	no review
Medik8	Medik8 R-Retinoate Intense	50	142.47	237.45	5	9
Neocutis	Neocutis Bio Serum Firm 30ml	30	239.45	239.45	no rating	no review
Lancer	Lancer Skincare Lift Serum Intense (30ml)	30	259.95	259.95	no rating	no review
RéVive	RéVive Perfectif Even Skin Tone Serum	30	259.95	259.95	no rating	no review
Lancôme	Lancôme Absolue Serum Star 30ml	30	265.95	265.95	5	1
Chantecaille	Chantecaille Bio Lifting Serum+ 30ml	30	275.95	275.95	no rating	no review
Erno Laszlo	Erno Laszlo Phormula 3-9 Repair Serum (1oz)	30	327.95	327.95	5	1
La Mer	La Mer The Lifting Contour Serum	30	333.45	333.45	no rating	no review
La Mer	La Mer The Regenerating Serum 30ml	30	333.45	333.45	no rating	no review
Shiseido	Shiseido Future Solution LX Intensive Firming Contour Serum 50ml	50	206.97	344.95	5	1
Natura Bissé	Natura Bissé Inhibit Exclusive High Definition Serum 30ml	30	391.45	391.45	3	2
111SKIN	111SKIN Celestial Black Diamond Serum 30ml	30	406.95	406.95	no rating	no review
RéVive	RéVive Intensité Complete Anti-Aging Serum 30ml	30	429.45	429.45	no rating	no review
						4681.00

Appendix 2 – Normality Test before Kruskal-Wallis

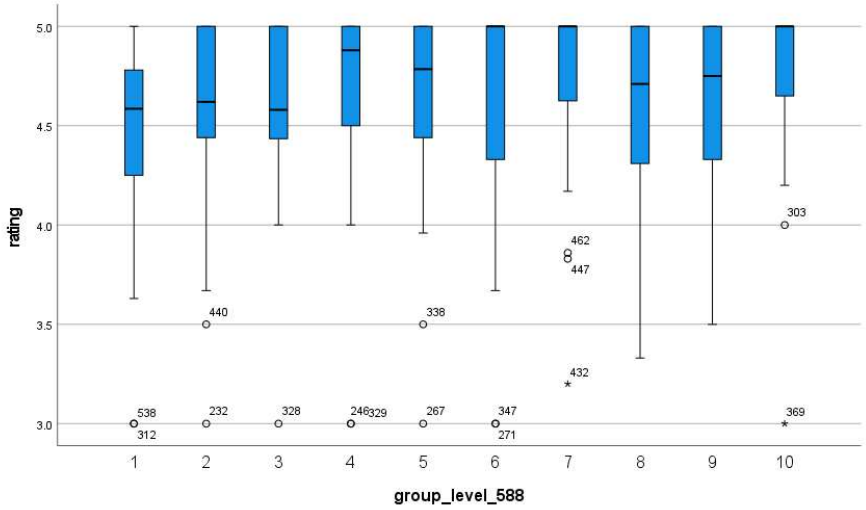
Descriptives

	group_level_588			Statistic	Std. Error
rating	1	Mean		4.49	.063
		95% Confidence Interval for Mean	Lower Bound	4.36	
			Upper Bound	4.61	
		5% Trimmed Mean		4.53	
		Median		4.59	
		Variance		.201	
		Std. Deviation		.448	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-1.612	.337
		Kurtosis		3.252	.662
	2	Mean		4.55	.078
		95% Confidence Interval for Mean	Lower Bound	4.39	
			Upper Bound	4.71	
		5% Trimmed Mean		4.60	
		Median		4.62	
		Variance		.223	
		Std. Deviation		.472	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-1.418	.388
		Kurtosis		2.240	.759
	3	Mean		4.58	.066
		95% Confidence Interval for Mean	Lower Bound	4.45	
			Upper Bound	4.71	
		5% Trimmed Mean		4.62	
		Median		4.58	
		Variance		.175	
		Std. Deviation		.418	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-1.486	.374
		Kurtosis		3.847	.733
	4	Mean		4.65	.088
		95% Confidence Interval for Mean	Lower Bound	4.47	
			Upper Bound	4.83	
		5% Trimmed Mean		4.72	
		Median		4.88	
		Variance		.272	
		Std. Deviation		.522	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-2.035	.398
		Kurtosis		4.164	.778
	5	Mean		4.63	.075
		95% Confidence Interval for Mean	Lower Bound	4.48	
			Upper Bound	4.78	
		5% Trimmed Mean		4.69	
		Median		4.79	
		Variance		.216	
		Std. Deviation		.465	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-1.702	.383
		Kurtosis		3.231	.750
	6	Mean		4.61	.099
		95% Confidence Interval for Mean	Lower Bound	4.41	
			Upper Bound	4.81	
		5% Trimmed Mean		4.68	
		Median		5.00	
		Variance		.335	
		Std. Deviation		.579	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-1.530	.403
		Kurtosis		1.676	.788
	7	Mean		4.75	.068
		95% Confidence Interval for Mean	Lower Bound	4.61	
			Upper Bound	4.89	
		5% Trimmed Mean		4.81	
		Median		5.00	
		Variance		.168	
		Std. Deviation		.410	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		0	
		Skewness		-2.270	.393
		Kurtosis		5.563	.768
	8	Mean		4.55	.096
		95% Confidence Interval for Mean	Lower Bound	4.36	
			Upper Bound	4.75	
		5% Trimmed Mean		4.59	
		Median		4.71	
		Variance		.285	
		Std. Deviation		.533	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-1.027	.421
		Kurtosis		-.085	.821
	9	Mean		4.61	.073
		95% Confidence Interval for Mean	Lower Bound	4.46	
			Upper Bound	4.75	
		5% Trimmed Mean		4.64	
		Median		4.75	
		Variance		.192	
		Std. Deviation		.438	
		Minimum		4	
		Maximum		5	
		Range		2	
		Interquartile Range		1	
		Skewness		-1.003	.393
		Kurtosis		.080	.768
	10	Mean		4.75	.096
		95% Confidence Interval for Mean	Lower Bound	4.55	
			Upper Bound	4.95	
		5% Trimmed Mean		4.83	
		Median		5.00	
		Variance		.221	
		Std. Deviation		.470	
		Minimum		3	
		Maximum		5	
		Range		2	
		Interquartile Range		0	
		Skewness		-2.655	.472
		Kurtosis		8.075	.918

Tests of Normality

	group_level_588	Kolmogorov-Smirnov[a] Statistic	df	Sig.	Shapiro-Wilk Statistic	df	Sig.
rating	1	.172	50	<.001	.857	50	<.001
	2	.172	37	.007	.850	37	<.001
	3	.167	40	.006	.835	40	<.001
	4	.251	35	<.001	.704	35	<.001
	5	.213	38	<.001	.795	38	<.001
	6	.308	34	<.001	.716	34	<.001
	7	.284	36	<.001	.668	36	<.001
	8	.218	31	<.001	.811	31	<.001
	9	.184	36	.003	.846	36	<.001
	10	.326	24	<.001	.608	24	<.001

a. Lilliefors Significance Correction



Appendix 3 - Independent-Samples Kruskal-Wallis Test

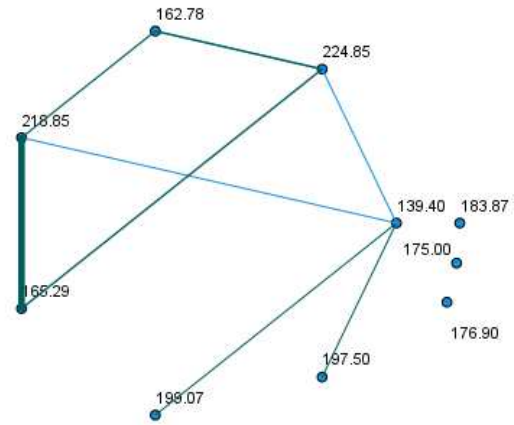
Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of rating is the same across categories of group_level_588.	Independent-Samples Kruskal-Wallis Test	.008	Reject the null hypothesis.

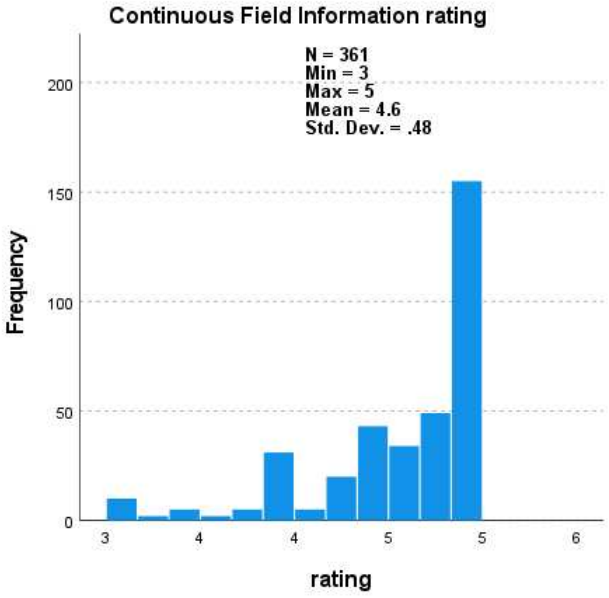
a. The significance level is .050.

b. Asymptotic significance is displayed.

Pairwise Comparisons of group_level_588



Each node shows the sample average rank of group_level_588.



Pairwise Comparisons of group_level_588

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
1-2	-23.384	21.963	-1.065	.287	1.000
1-3	-25.887	21.484	-1.205	.228	1.000
1-8	-35.600	23.152	-1.538	.124	1.000
1-9	-37.503	22.137	-1.694	.090	1.000
1-5	-44.468	21.796	-2.040	.041	1.000
1-4	-58.100	22.320	-2.603	.009	.416
1-6	-59.674	22.513	-2.651	.008	.362
1-7	-79.447	22.137	-3.589	<.001	.015
1-10	-85.454	25.150	-3.398	<.001	.031
2-3	-2.504	23.101	-.108	.914	1.000
2-8	-12.216	24.660	-.495	.620	1.000
2-9	-14.119	23.709	-.596	.552	1.000
2-5	-21.085	23.391	-.901	.367	1.000
2-4	-34.716	23.881	-1.454	.146	1.000
2-6	-36.290	24.060	-1.508	.131	1.000
2-7	-56.063	23.709	-2.365	.018	.812
2-10	-62.070	26.544	-2.338	.019	.872
3-8	-9.713	24.234	-.401	.689	1.000
3-9	-11.615	23.267	-.499	.618	1.000
3-5	-18.581	22.942	-.810	.418	1.000
3-4	-32.212	23.441	-1.374	.169	1.000
3-6	-33.786	23.624	-1.430	.153	1.000
3-7	-53.560	23.267	-2.302	.021	.960
3-10	-59.567	26.150	-2.278	.023	1.000
8-9	-1.903	24.815	-.077	.939	1.000
8-5	8.868	24.511	.362	.717	1.000
8-4	22.500	24.979	.901	.368	1.000
8-6	24.074	25.151	.957	.338	1.000
8-7	43.847	24.815	1.767	.077	1.000
8-10	-49.854	27.536	-1.810	.070	1.000
9-5	6.966	23.555	.296	.767	1.000
9-4	20.597	24.041	.857	.392	1.000
9-6	22.171	24.220	.915	.360	1.000
9-7	41.944	23.871	1.757	.079	1.000
9-10	-47.951	26.689	-1.797	.072	1.000
5-4	13.632	23.727	.575	.566	1.000
5-6	-15.205	23.908	-.636	.525	1.000
5-7	-34.979	23.555	-1.485	.138	1.000
5-10	-40.986	26.406	-1.552	.121	1.000
4-6	-1.574	24.387	-.065	.949	1.000
4-7	-21.347	24.041	-.888	.375	1.000
4-10	-27.354	26.841	-1.019	.308	1.000
6-7	-19.774	24.220	-.816	.414	1.000
6-10	-25.781	27.001	-.955	.340	1.000
7-10	-6.007	26.689	-.225	.822	1.000

Each row tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same.

Asymptotic significances (2-sided tests) are displayed. The significance level is .050.

a. Significance values have been adjusted by the Bonferroni correction for multiple tests.

Appendix 4 – Programming with Python

Part 1: Data scraping

```
import requests
from bs4 import BeautifulSoup
import pandas as pd
url = 'https://www.lookfantastic.com/health-beauty/face/skincare-products/specific-
care/serums.list?' \
'pageNumber=25&settingsSaved=Y&shippingcountry=CN&sortOrder=priceAscending&swit
chcurrency=EUR'
r = requests.get('http://localhost:8050/render.html',params = {'url':url, 'wait':2})
soup = BeautifulSoup(r.content, 'lxml')
print(r.status_code)
# print(r.text)

serumlist = list()
productlist = soup.find_all('li', class_='productListProducts_product ')
for item in productlist:
    name = item.find('h3', class_='productBlock_productName').text.strip()
    price = item.find('span', class_='productBlock_priceValue').text.strip()
    try:
        review_count = item.find('span', class_='productBlock_reviewCount').text.strip()
    except:
        review_count = 'no review'
    try:
        rating = item.find('span',class_='productBlock_ratingValue').text.strip()
    except:
        rating = 'no rating'
    # print(name,price,review_count,rating)

    serum = {
        'name': name,
        'price': price,
        'rating':rating,
```

```
        'reviews':review_count,
    }
    # print(serum)
    serumlist.append(serum)
df = pd.DataFrame(serumlist)
df.to_excel('Lookfantastic_ascending_p25.xlsx',index=False)
print('Fin.')
```

Part 2: Text processing and analysis for Objective 4 – Keywords Extraction

```
# Text processing for Objective 4: in a word-level

import xlrd
book = xlrd.open_workbook(r'E:\Database\Thesis.xlsx')
page = int(input('You want to extract the key words of Group:'))
sheet =book.sheet_by_index(page+1)
Body_raw = " ".join(sheet.col_values(colx=7))

# Step 1：Eliminate blank space and capitalization
Body = Body_raw.lstrip().rstrip().lower()

# Step 2：Tokenization
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
AI_tokens = word_tokenize(Body)

# Step 3: Punctuation
import re
punctuation = re.compile(r'[]["` -.?!,:“;(•)’|0-9]')
post_punctuation = list()
for words in AI_tokens:
```

```
    word = punctuation.sub('',words)
    if len(word) > 2:  #这里设置为 2 是为了晒出 nt 这个无意义字符
        post_punctuation.append(word)


# Step 4: Stopwords
post_stopwords = [word for word in post_punctuation if word not in
stopwords.words('english')]

# Step 5：post tag
post_tag = nltk.pos_tag(post_stopwords)

# Step 6：Lemmatization
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
def get_wordnet_pos(tag):
    if tag.startswith('J'):
        return wordnet.ADJ
    elif tag.startswith('V'):
        return wordnet.VERB
    elif tag.startswith('N'):
        return wordnet.NOUN
    elif tag.startswith('R'):
        return wordnet.ADV
    else:
        return None

wnl = WordNetLemmatizer()

lemmas_sent = list()
for tag in post_tag:
    if tag[1].startswith('N'): # NOUN
```

```
        wordnet_pos = get_wordnet_pos(tag[1]) or wordnet.NOUN
        lemmas_sent.append(wnl.lemmatize(tag[0], pos=wordnet_pos)) #词形还原


# Text analysis for Objective 4: Extract General keywords

counts = dict()
for word in lemmas_sent:
    counts[word] = counts.get(word, 0) + 1

lst = list()
for keyword, count in counts.items():
    lst.append((count,keyword))
lst.sort(reverse=True)   # sort_list is a list of tuples

sumfreq = list()
for count,word in lst[:len(lst)]:
    sumfreq.append(count)

n = 20  # input the number of keyword to be presented
final = list()
for count,word in lst[:n]:
    final.append(word)

for count,word in lst[:n]:      # slicing the sort_list
    print(word,count,'percent: {:.2f}%'.format(count/sum(sumfreq)))

# Text analysis for Objective 5: Extract positive and negative keywords

sentiment_dictionary = {}
for line in open(r'E:\Database\AFINN-111.txt'):
    word,score = line.split('\t')
    sentiment_dictionary[word] = int(score)
```

```
positive_word_list = list()
negative_word_list = list()
for word in lemmas_sent:
    score = sentiment_dictionary.get(word, 0)
    if score > 0:
        positive_word_list.append(word)
    if score < 0:
        negative_word_list.append(word)

import pandas as pd
from pandas import DataFrame

top_positive_word = pd.value_counts(positive_word_list).head(5)
top_negative_word = pd.value_counts(negative_word_list).head(5)
print(top_positive_word,top_negative_word)
```

Part 3: Text processing and analysis for Objective 5 – Sentiment Polarity

```
# Text processing for Objective 5: in a sentence-level
import xlrd
book = xlrd.open_workbook(r'E:\Database\Thesis.xlsx')
page = int(input('You want to calculate the overall sentiment score of Group:'))

sheet =book.sheet_by_index(page+1)
Body_raw = sheet.col_values(colx=7)

import nltk
from nltk.tokenize import sent_tokenize
from nltk.tokenize import word_tokenize

review_polarity_list =list()
```

```
for review in Body_raw[1:]:
    Body = review.lstrip().rstrip().lower()
    AI_tokens = sent_tokenize(Body)

    sent_polarity_list = list()

    for sent in AI_tokens:
        words = word_tokenize(sent)

        import re
        punctuation = re.compile(r'[]["` -.?!,:“;(•)’|0-9]')
        post_punctuation = list()
        for word in words:
            actual_word = punctuation.sub('',word)
            if len(actual_word) > 2:
                post_punctuation.append(word)

        from nltk.corpus import stopwords
        post_stopwords = [actual_word for actual_word in post_punctuation if actual_word not
in stopwords.words('english')]

        post_tag = nltk.pos_tag(post_stopwords)

        from nltk.stem import WordNetLemmatizer
        from nltk.corpus import wordnet

        def get_wordnet_pos(tag):
            if tag.startswith('J'):
                return wordnet.ADJ
            elif tag.startswith('V'):
                return wordnet.VERB
            elif tag.startswith('N'):
                return wordnet.NOUN
            elif tag.startswith('R'):
```

```
            return wordnet.ADV
        else:
            return None
    wnl = WordNetLemmatizer()
    lemmas_sent = list()
    for tag in post_tag:
        wordnet_pos = get_wordnet_pos(tag[1]) or wordnet.NOUN
        lemmas_sent.append(wnl.lemmatize(tag[0], pos=wordnet_pos))  #

    sent_words = ' '.join(lemmas_sent)



   # Text analysis for Objective 5:
    Calculate sentiment polarity score using TextBlob library

    from textblob import TextBlob

    blob = TextBlob(sent_words)
    sent_sentiment = blob.sentiment.polarity
    sent_polarity_list.append(sent_sentiment)

  from numpy import *
  review_polarity = mean(sent_polarity_list)
  review_polarity_list.append(review_polarity)

  print(review)
  print('percent: {:.2f}'.format(review_polarity))

print(review_polarity_list)

group_polarity = mean(review_polarity_list)
print("Group Sentiment：",'percent: {:.2f}'.format(mean(group_polarity)))
```