

**7053 SSL Master’s Dissertation**

Student’s Family Name:

Theeyattuparambil John

First Name:

Clints

Student ID:

13518992

Course:

MSc. Business Analytics

Supervisor:

Syed Rizvi

Dissertation Title

**Using social media analytics to understand UK retail customer sentiment for better marketing strategies.**

Declaration

I certify that this dissertation is my own work. I have read the University regulations concerning plagiarism.

**I am willing to allow Coventry Business School to use my dissertation as a sample for future students.**

Signed: Clints Date: 4th December 2023

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# Abstract

This research explores how major UK fashion and grocery retailers can leverage social media analytics to gain customer insights and improve marketing strategies. Sentiment analysis and text mining of 1000 Twitter and Instagram comments per leading grocery and fashion brand unveils consumer perceptions. Findings reveal overwhelming negative sentiment - 60-70% of remarks were complaints. Key fashion frustrations centred on product quality, sizing, refunds and delivery; grocery grievances highlighted ordering, communication and customer service deficiencies. By targeting these specific pain points exposed through social listening, retailers can enhance relevance. Ultimately, systematically mining the abundance of organic social data promises improved customer centricity, loyalty and performance if analytics directly inform merchandising, innovation and engagement initiatives. This study confirms the immense yet overlooked potential in online commentary.

# 1. Introductory Chapter

## 1.1 Introduction

The rise of social media gives a tremendous opportunity for UK retailers to acquire a competitive advantage by better understanding their customers. With increased competition in the retail sector, brands require compelling ways to distinguish out. Retailers can measure and analyse consumer sentiment - the opinions, attitudes, feelings, and preferences expressed about products and services online - by tapping into the richness of social data collected from platform users. These insights into the customer thinking can help design targeted, customer-centric initiatives to increase satisfaction and sales. Implementing data-driven social listening allows merchants to tailor their offerings and experiences to exactly what their customers think and want. This is especially significant for the UK's fashion and grocery stores, which are competing for consumer attention and loyalty.

A graph of a number of blue bars

Description automatically generated with medium confidence

Figure 1 Leading ten retailers based on sales in UK in 2022/2023 (Sabanoglu, 2023)

## 1.2 Background of the study

The retail industry in the UK faces fierce competition, with giants like Tesco, Sainsbury's, Asda and Morrison intensely battling for customers (Sharma & Jain, 2020). The landscape has transformed through online shopping and social media. Before purchasing, consumers research products and discuss experiences across digital platforms – key retailer touchpoints are Facebook, Twitter, Instagram, etc. (Sharma & Jain, 2020). The conversations on these channels provide a vital yet underutilized opportunity. By analysing this unstructured textual data through sentiment analysis, retailers can gain integral consumer insights. Positive sentiment signals favourable perceptions or experiences; negative emotions relate to dissatisfaction or unmet expectations. Examining social media followers' sentiments and reactions allows strategic identification of pain points and potential improvements to address unfulfilled wants for competitive advantage (Liu et al., 2019).

In summary, leveraging analytical tools provides deep awareness of evolving preferences, pain points, and loyalty drivers. This allows refinement of offerings, service, and marketing for higher engagement, satisfaction and lifetime value (Liu et al., 2019). With consumers fluidly researching and purchasing across online and offline touchpoints, tapping into unfiltered social data is crucial for intelligence (Sharma & Jain, 2020). Broader listening tracks shifts across groups; targeted analytics provide granular insights on specific segments’ needs – delivering complete emotional intelligence. Ultimately, frequent analytics enables rapid issue detection and response, while recognizing emergent successes to amplify. Lacking such solutions, retailers will rapidly lose relevance and sales (Liu et al., 2019).

## 1.3 Rationale of the study

The advent of social media platforms like Instagram, Facebook and Twitter have transformed how consumers discover, research and engage with brands, products and services (Erkan & Evans, 2018). Studies show over 82% of UK consumers leverage these technologies to investigate retailers before buying. Consequently, continually monitoring, analysing and deriving intelligence from the exponentially growing amount of organic, unstructured shopper data and sentiment manifesting on public social channels has become vital for customer-focused UK retail strategy. However, extracting meaningful insights from the volume of daily social conversations requires specialized analytics techniques and resources. Recent surveys highlight a capability gap - with research indicating only a limited percentage of UK retail marketers currently leverage automated sentiment analysis tools to unlock revealed consumer perceptions in social data (Cirqueira et al., 2020). Retailers who fail to listen risk losing visibility into shifting preferences, emerging pain points and opportunities. Alternatively, brands able to tap into analytics to translate unfiltered social data into actionable business intelligence can reap benefits. For instance, by applying machine learning and natural language processing to gauge sentiment levels and derive themes from collective follower commentary over time, retailers can gain visibility into evolving customer attitudes, satisfaction, brand affinities, product reactions and more (Das et al., 2022). Surface-level listening provides a real-time barometer into subjective perceptions that may preview declining sales, loyalty and retention metrics before customers defect. Deeper mining can uncover specific pain points around issues like product features, online experience frustrations and delivery policies for targeted mitigation to lift lifetime value.

## 1.4 Scope of the study

This study focuses on major UK retail brands in the grocery (supermarkets) and fashion (apparel) sectors. These industries face intense competition for consumer mindshare and require insights into evolving preferences to retain market position. The research scope concentrates analytic attention on Twitter and Instagram, used by over 70% of UK shoppers to engage leading retailers. This vibrant social discourse presents a valuable data source for text mining, NLP and sentiment analysis to translate commentary into actionable intelligence. The scope includes assessing case studies where deploying these techniques empowered brands to guide targeted improvements across marketing, product innovation and customer experience. Criteria account for constraints managers encounter embedding insights across complex organizations. Concentrating on UK regions controls for cultural variances in social media usage that may impact analysis. Selected cases cover prominent UK fashion chains and leading multichannel grocery brands as examples within competitive British industries. The goal is informing analytical capability building for wider domestic sectors based on the focused evaluation of platforms and practices where social data analytics has gained measurable traction. In summary, this concentrated scope supports an informed assessment of adoption considerations for UK retail peers contemplating similar consumer-centric strategies.

## 1.5 Motivation for the work

The rise of social media provides a vital yet underutilized avenue for UK retailers to gain competitive edge by analysing unfiltered consumer perspectives emerging through online commentary. As consumers increasingly leverage platforms like Twitter and Instagram to research purchases and voice opinions, the exponential growth of user-generated content offers a wealth of revelatory shopper insights untapped at scale. By utilizing text mining, sentiment analysis and other analytical techniques to decode embedded perceptions within this organic social discourse, UK fashion and grocery merchants can uncover granular intelligence into evolving preferences, frustrations and affinities. Deriving actionable insights empowers brands to convert unstructured commentary into targeted, customer-centric marketing strategies that enhance relevance, foster advocacy and maximize lifetime value. Effectively mining sentiments from social data is especially crucial for UK retailers facing fierce competition and needing to distinguish offerings in crowded markets. My work is thus motivated by this immense yet overlooked potential within abundantly available but complex consumer social data to unveil integral intelligence for data-driven retail strategies aimed at acquisition, conversions and loyalty.

## 1.6 Significance of the work

This research has immense significance as social media analytics remains an overlooked goldmine of revelatory shopper insights that can profoundly guide UK retail strategy. As consumers increasingly leverage platforms like Twitter and Instagram to voice opinions, compare experiences, and influence one another, the exponential growth of organic user-generated content represents a wealth of consumer perceptions around needs, frustrations and brand sentiment manifesting online. By effectively mining this data at scale using the latest text analytics techniques like sentiment analysis to decode embedded judgments within comments, retailers can derive nuanced emotional intelligence around evolving preferences, dissatisfactions and affinity drivers unavailable through traditional channels. While major studies demonstrate this potential for competitive intelligence and real-time issue identification, industry surveys reveal most UK retail marketers do not utilize automated social listening tools to systematically transform this abundance of unfiltered commentary into actionable insights. This gap motivated this timely research focused on fashion and grocery leaders to expose the customer retention and lifetime value benefits possible when social data is strategically mined rather than simply monitored at surface levels. Ultimately, this exploration of platforms and practices signals pathways for retail peers to follow towards enhanced relevance.

## 1.7 Research Aim

The aim of this research is to critically evaluate how major UK fashion and grocery retailers can effectively leverage social media analytics techniques to derive actionable insights from unstructured shopper sentiment data for data-driven marketing and merchandising decisions that enhance financial performance.

## 1.8 Research Questions

a) How can social media analytics be utilized to understand UK retail customer sentiment?

b) What insights can be gained from social media analytics to inform marketing strategies for UK retailers?

c) How effective are social media analytics in improving marketing strategies and performance for UK retailers?

## 1.7 Research Objectives

* To analyse social media data from major platforms, especially Twitter (X) and Instagram, to identify key themes, trends, and insights into UK retail customer sentiment.
* To explore the use of various social media analytics techniques like text analytics, natural language processing, and sentiment analysis for analysing UK retail customer sentiment.
* To critically evaluate the challenges faced by UK retail brands through social media analytics for gaining actionable customer and marketing insights.
* To critically review existing academic literature on utilizing social media analytics to understand customer sentiment and inform marketing strategies.

## 1.8 Thesis Structure

The thesis is organized into 5 chapters - introductory, literature review, methodology, findings and analysis, conclusions and recommendations. The introductory chapter presents background, rationale, scope, motivation, research questions, objectives and significance. The literature review critically evaluates prior academic work on utilizing social media analytics and text mining to understand customer sentiment and inform marketing strategy. The methodology chapter details the interpretivist philosophy, inductive-deductive mixed methods approach, and qualitative and quantitative techniques employed for social data analysis. The findings and analysis chapter applies sentiment assessment and text mining on sample social content to derive actionable insights on UK retail customer perceptions. Finally, the conclusions summarize key discoveries while recommendations suggest strategies for fashion and grocery brands to address identified experience gaps, integrating social intelligence for enhanced relevance.

# 2. Literature review

Social media has become an indispensable component of customers' daily lives, giving outlets for them to communicate their thoughts, reviews, complaints, and sentiments about businesses, products, and services. With millions of users contributing massive amounts of unstructured textual data every day, social media is a wealth of information for businesses looking to better understand their clients and customise their marketing tactics appropriately (Choi et al., 2020). In the United Kingdom, the retail industry is fiercely competitive. Tesco, Sainsbury's, Asda, and Morrisons all battle for market share. Online shopping and social media have altered the retail industry. Consumers now research products and share their experiences online before making a purchase. Platforms like Facebook, Twitter, and Instagram act as crucial links between businesses and their customers (Rahman & Ekereuke, 2023).

## 2.1 Sentimental Analysis

Sentiment analysis, commonly referred to as opinion mining, is an important technique in social media analytics. It entails systematically identifying, extracting, and studying affective states and subjective information through text analysis and natural language processing. Specifically, it enables organisations to analyse online interactions to assess overall sentiment about products, brands, or services (Liu, 2022). In particular, sentiment analysis is used to understand public and consumer opinions in marketing, customer service, social media monitoring, and other fields of study (Liu, 2022). For example, analysis of social media conversations can provide consumer insights. Positive sentiment frequently suggests positive consumer experiences, while negative emotions are typically related with dissatisfaction. This unstructured textual data supports retailers in discovering client pain areas and unfulfilled desires (Sharma & Jain, 2020). The sentiment analysis process consists of numerous key processes, including data collection, data preparation, analysis and scoring, and data visualisation and interpretation. First, data collection entails gathering primary datasets from various social media networks, such as Twitter, Facebook, Reddit, and TripAdvisor, which are frequently used for machine learning algorithms. Next, data preprocessing entails cleaning the data samples, removing extraneous pronunciations, hashtags, URLs, text correction, stop words, and tokenization. After that, analysis and scoring entail employing various methods or models to handle the pre-processed dataset, with three main approaches being lexicon-based techniques, machine-learning-based techniques, and hybrid techniques. Finally, data visualisation and interpretation entails visualising results in charts and graphs to acquire simple insights (Xu et al., 2022).

## 2.2 Social Media Analytics

Social media analytics is the act of acquiring and analysing data from social media sources to make informed business decisions. It entails creating and testing tools to gather, monitor, analyse, summarise, and visualise social media data in response to specific application needs (Wang et al., 2020). Social media analytics should be employed in marketing research at both the technical and strategic levels. It can result in changes in organisational practises such as data-driven, internal, and holistic approaches, as well as cultural and structural modifications (Wang et al., 2020). The ever-changing technological elements of social media analytics drive organisations to develop adaptable and quick marketing tactics. Real-time analytics can assist businesses in dealing with user reactions and behaviours, while linguistic analytics can disclose context-dependent cultural aspects. To get the most benefits, businesses should build a technological knowledge base and promote alignment between social media analytics and marketing and organisation (Wang et al., 2020). Social media analytics (SMA) technologies assist researchers and data scientists in analysing client behaviour on social networking platforms. They are classified as built-in programmes and cross-platform equipment. Built-in SMA programmes analyse social networking data on profiles, but their capability is limited in comparison to other specialised tools (Smith, Yakuve, & O’brian, 2022). SMA treatments assist internet retailers in connecting with the proper audiences and improving consumer impression by providing insights into behaviour patterns and personal preferences. They improve online retail business options through personalization, co-branded campaigns, interest-generating merchandise, survey research, targeted advertising, and influencer mapping. SMA also allows for improved survey research, targeted advertising, and influencer mapping, guaranteeing products are available and purchased while saving money on online marketing (Smith, Yakuve, & O’brian, 2022).

A diagram of a data processing process

Description automatically generated

Figure 2 The suggested big data-assisted social media analytics for business (BD-SMAB) model's design. (Zhang et al., 2022).

Figure 2 depicts big data-assisted social media analytics for business model design. The BD-SMAB model is a framework for enterprises to use big data for social media analytics that consists of four steps: intelligence, decision comprehension and modelling, data gathering and planning, planning, constructing prototypes, and database creation (Zhang et al., 2022).

## 2.3 Text Mining

Learning valuable information and knowledge from textual data is the main goal of the discipline of text mining research. Specifically, it includes analysing vast amounts of semi-structured or unstructured text material using methods and algorithms in order to find important patterns and trends. In particular, extraction of relevant and interesting information from large volumes of textual data can be made easier with the use of text mining techniques, which can improve retrieval speed and efficiency (Ajay Jadhav et al., 2023). Furthermore, text mining is a computational process that converts unstructured text data into structured data, recognising patterns and relationships, and transforming the information into valuable insights for predictive modelling and knowledge management (Jo, 2019). Additionally, it is a rapidly growing field in computer science and has various applications, such as categorizing research abstracts based on their content (Choi et al., 2023). In contrast, the type of data handled by data mining and text mining differs. To illustrate, text mining deals with unstructured data found in documents, emails, social media, and the web, whereas data mining deals with structured data from systems such as databases, spreadsheets, ERP, CRM, and accounting applications (Hassani et al., 2020). Moreover, topic modelling is a widely used tool for extracting important topics from social networks and understanding large amounts of unstructured data. It is especially useful in sentiment analysis, customer behaviour, and forecasting, particularly in online retailing where extracting relevant information and identifying customer concerns is difficult (Ibrahim & Wang, 2019). Additionally, a panel of specialists is involved in integrating text-mining tools with qualitative methods. This method reduces the shortcomings of quantitative and qualitative approaches, such as concerns with reliability and validity, as well as potential bias in future industrial decisions. Furthermore, the patent-based text mining approach assists specialists in learning about critical retailing technology and probable future developments (Ozcan et al., 2022).

Text mining has a number of difficulties. The unstructured and diverse nature of research publications is a significant obstacle that makes mass information extraction challenging (Ramachandran & Ramachandran, 2022). The increasing quantity and unstructured character of text corpora, including social media content, need the use of analysis methods other than conventional human coding (Bittermann & Fischer, 2023). Additionally, the application of machine learning algorithms and deep learning in text mining has limitations and hazards, particularly in terms of accountability, validity, and reliability (Kononova et al., 2021).

Text mining has a number of difficulties. The unstructured and diverse nature of research publications poses a major challenge that makes mass information extraction difficult (Ramachandran & Ramachandran, 2022). Additionally, the increasing volume and unstructured nature of text corpora, including social media content, necessitate the use of analytical methods beyond conventional human coding (Bittermann & Fischer, 2023). Furthermore, the application of machine learning algorithms and deep learning in text mining has certain limitations and risks, especially regarding accountability, validity, and reliability (Kononova et al., 2021).

Text mining can be used to improve customer service by analysing customer reviews and feedback. Specifically, customer reviews can be used to uncover the characteristics of service quality using text mining techniques such as Latent Dirichlet Allocation (LDA) (ÇULLU & OKURSOY, 2023). This enables organisations to pinpoint specific areas where customers are having issues or are dissatisfied; for instance, common problems include system availability, responsiveness, erroneous updates, login issues, and dependability (Hussain et al., 2023). By being aware of these challenges, managers can acquire valuable insights into how to improve the service experience and properly handle customer concerns (Mejia et al., 2021). Additionally, text mining can be used to classify questions and replies in chatbot systems, thereby allowing for the automatic generation of relevant responses to client requests (Massaro et al., 2022). Using this capability helps provide consumers with efficient and accurate support, thus enhancing the overall customer service experience.

## 2.4 Consumer Behaviour

Consumer behaviour relates to consumers activities and decision-making processes when purchasing goods or services. It entails evaluating and comparing the benefits of various items and is influenced by a variety of elements such as social reference groups, age, social perception, and purchasing power (Fadilah et al., 2023). Consumer decision-making refers to the consumer patterns that precede, determine, and follow the decision process for acquiring need-satisfying items, ideas, or services. According to recent studies, social media has a substantial impact on consumer behaviour by offering instant access to information, influencing product choice and purchase behaviour, and establishing a participatory culture in which users network and exchange knowledge (Voramontri & Klieb, 2019). Furthermore, Chaudhary et al (2021) analysed consumer behaviour and improved brand tactics using big data from social media networks. They gathered data from 8434 new businesses and created a machine learning model to predict involvement levels. Deep learning was discovered to be the most accurate way for predicting engagement. Additionally, the study also discovered that tweets, retweets, and likes had a substantial influence on the usefulness of social media marketing behaviour (Chaudhary et al., 2021).

A diagram of a social media diagram

Description automatically generated

Figure 3 Consumer perception and attitude (Chaudhary et al., 2021).

Moreover, Figure 3 depicts how consumer perception and attitude influence consumer behaviour, which has an impact on social media. The total impact of consumer behaviour on social media is studied using big data analytics (Chaudhary et al., 2021). Authenticity, trustworthiness, and openness are critical in developing confidence in Social Media Influencers (SMIs). Micro-influencers boost authenticity by making genuine connections with their followers' needs. Follower evaluations and transparent disclosure practises contribute greatly to overall trust dynamics, highlighting the multidimensional nature of trust in the field of influencer marketing (Lee et al., 2021).

## 2.5 Sentiment Analysis of Twitter(X) Data

Twitter is a promising area for sentiment analysis, a branch of linguistics that employs deep learning to extract opinions and feelings from textual data. This approach detects sentiment polarity in social media messages by combining sentiment detection with conversation reconstruction modules. Google and Microsoft have developed sentiment analysis technologies to aid in their industrial and commercial activities (Wang et al., 2022).

A diagram of a process

Description automatically generated

Figure 4 Operation flow of twitter sentimental analysis (Wang et al., 2022)

Sentiment analysis and opinion mining on social media sites, including Twitter, are being conducted by researchers using deep learning algorithms including Word2Vec, Glove, Recurrent Neural Network (RNN), Convolutional Neural Network (CNN), and Gated Recurrent Unit (GRU) (Goularas & Kamis, 2019). NLP's (natural language processing) ability to identify polarity in words and documents is revolutionising sentiment analysis on Twitter. This approach improves sentiment identification accuracy by automatically categorising tweets as positive, negative, or neutral using a combination of domain ontology and natural language processing techniques (Hasan et al., 2019). Sentiment analysis uses a variety of techniques, including the development of sentiment lexicons, user summarization systems, and the use of unsupervised learning algorithms, to assess sentiment and binary classification. The investigation goes so far as to include soft computing methods like fuzzy logic and neural networks. This all-encompassing strategy seeks to decipher and analyse attitudes in textual data by combining language analysis with cutting-edge computer techniques to provide a sophisticated understanding (Prema Arokia Mary et al., 2021). Machine learning algorithms such as naive Bayes, logistic regression, and support vector machines help improve sentiment analysis on Twitter data. These classifiers can effectively categorise tweets as positive or negative sentiment without the use of a preexisting word dictionary, providing a faster and more accurate approach to sentiment research (Mishra, 2023).

## 2.6 Ethics in mining social media data

Data mining ethics entails evaluating the ethical implications and issues that occur when doing data mining research or employing data mining techniques. It is critical to guarantee that data mining practises follow ethical norms and preserve individuals' rights and privacy (Calvo & Egea-Moreno, 2021).Ethical guidelines for using social media data in research are crucial due to complexity, access inequalities, interpretation, and unclear boundaries between public and private spaces, as well as ownership and intellectual property issues. The Research Councils United Kingdom (RCUK), a strategic partnership of seven UK research councils, is examining the impact of social media research on information privacy, confidentiality, and ownership, highlighting the challenges of effective oversight in this multidisciplinary field (Taylor & Pagliari, 2017). Because of the use of third-party data on social media sites, marketers have privacy issues. Normative, positive, consumer, and virtue ethics are all debated in marketing ethics. Individuals expect privacy even when publicly available data is available. According to research, marketers frequently fail to identify ethical difficulties, emphasising the importance of knowing marketing ethics in social media marketing (Jacobson et al., 2023). Maintaining compliance with the social media project's requirements necessitates close examination and stringent observance of the disciplinary measures' terms and conditions, especially when it comes to interactions with outside parties. To guarantee not just compliance but also the efficient handling of disciplinary proceedings inside the project's framework, it is imperative to carefully assess and follow the prescribed criteria, particularly when interacting with outside parties (Townsend & Wallace, 2016). Customer feedback and behaviour mining require ethical considerations because sensitive PII (personally identifiable information) data from social media and surveys can pose hazards. Privacy and anonymity are critical, especially when such data is exposed to new audiences. Filtering user-generated content and avoiding biased variables can assist prevent inaccurate outcomes (Deng, 2017). Data mining has the ability to extract significant insights and patterns from vast databases, but it also raises concerns about data privacy, discrimination, and data exploitation. Data mining researchers and practitioners must be aware of these ethical challenges and take appropriate action to address them. One strategy, for example, is to employ data mining techniques to detect anomalies and behaviour patterns that necessitate action to examine, correct, encourage, or expand ethical practises (Calvo & Egea-Moreno, 2021).

## 2.7 Marketing Management and Management information system

Marketing management and management information systems are critical for current corporate efficiency. Specifically, management information systems are essential for assessing the need for marketing information and enabling timely management decisions that benefit both the market and the customer (BLYZNIUK, 2023). These systems consist of organisational protocols that govern the flow of information between sellers and buyers, ensuring rapid and sensible information processing (Fu & Liu, 2023). As a result, managers can strategize competitive tactics and make quick decisions, thereby enhancing the company's market position and competitiveness (JI & JI, 2019). Additionally, a MIS can facilitate the development of competitiveness, the promotion of new business opportunities, and the enhancement of retail operations (Queiroz & Oliveira, 2014). Essentially, the purpose of a Management Information System (MIS) is to reduce uncertainty and minimise risk. It gives marketing decision-makers precise, up-to-date, and necessary information, which promotes increased efficacy and efficiency in modern organisational marketing management. In today's business frameworks, MIS plays a major role in increasing informed decision-making by providing dependable insights that improve operational and strategic understanding. (Rouissi, 2020).

Business decision-making systems include reviews of business management, business policies, plans, and goals, value analysis, market system method analysis, and organisational efficiency analyses. In contrast, corporate decision-making systems are computerized programs for processing and analysing data to create comprehensive reports (Yang et al., 2022). Specifically, the Management Information System (MIS) is a critical network for executives to use in making decisions and achieving organisational objectives. In particular, it provides data for operations planning and control, utilising computer technology for speed, accuracy, and data volume. Within organisations, MIS is used to support information required by all levels of management. Indeed, effective management is essential for the efficient and effective operation of MIS (Putri et al., 2022). Additionally, social media is an important part of B2B marketing, with 84% of C-level and VP-level buyers using it to make purchasing decisions. Similarly, social media is used by 83% of business marketers. The Covid-19 pandemic has heightened the significance of social media, with its role becoming increasingly important. However, the use of social media in business-to-business sales remains limited (Kumar & Sharma, 2022). Moreover, Inter-organizational Management Information Systems (MIS) are critical for social innovation because they enable businesses to manufacture goods that suit the needs of their customers. These systems convey information between organisations by utilising technology and intelligent computer systems, ensuring that technological developments are freely accessible. In comparison, profit-driven or competitive business-driven innovation is less efficient than social innovation, and effective projects necessitate a rich pool of knowledge linked to global information (Tang & Shao, 2019).

# 3. Methodology

## 3.1 Purpose of methodology

The methodology section is essential for explaining and supporting the exact research methodologies used to investigate a study's research questions and hypotheses. The methodology details the entire study strategy, including the rationale for using qualitative, quantitative, or mixed techniques approaches. It also specifies the exact data collecting and analysis procedures employed in accordance with the chosen strategy (Saunders et al., 2019).

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Figure 5 The research onion (Saunders et al., 2019)

According to Saunders et al. (2019), the technique must be in line with the research aims and the resources available. The "research onion" is a valuable foundation for constructing this methodology, with layers such as philosophy, approach, and strategy peeling back. By defining the research philosophy, assumptions regarding how evidence is perceived and what is regarded as genuine information are clarified. This informs decisions about the general reasoning strategy - deductive vs inductive. The approach chosen influences the sort of study plan, which in turn influences decisions on time horizons, data collecting, and analysis techniques that are aligned with available resources.

Thus, outlining a clear methodology is critical for justifying methodological decisions in order to provide valid answers to research questions. It also allows others to evaluate the appropriateness of the approaches employed.

## 

## 3.2 Research philosophy

Research philosophy is the process of gaining understanding and forming one's own opinion on a particular subject, particularly during the research process. It's possible that new information is only an expansion of existing knowledge rather than the discovery of entirely new hypotheses. Research philosophies come in a variety of forms, including as objectivism, positivism, interpretivism, and realism. Their various uses support the philosophical decision with respect to the selected research methodology (Saunders et al., 2019).

In terms of research methodology, this study explores the complex and culturally embedded character of social media comments by embracing an interpretivist research philosophy. Interpretivism, as espoused by Saunders et al. (2019), rejects the positivist idea that there are universal rules regulating social phenomena and instead emphasises the variety and subjectivity of individual viewpoints that people bring to their experiences. Interpretivism is consistent with the idea that opinions stated in comments are influenced by personal perceptions, societal norms, and values when applied to data from social media.

In summary, research philosophy represents the perspectives and beliefs that guide inquiry for new knowledge, underpinning the choice of methodology. This research adopts an interpretivist philosophy aligned with the aim of understanding subjective viewpoints expressed through complex social media discourse. As elucidated, interpretivism focuses on how personal lenses and sociocultural realities shape the situated, value-laden takes expressed online rather than seeking generalized rules of sentiment. Embracing interpretivism provides a paradigm for inductive analysis to unpack the embedded cognitive frames and contextual influences that drive the opinions captured through diverse social media commentary. Its emphasis on subjectivity and meaning-making constructs the philosophical foundation for examining the rich cognition permeating retail sentiments mentioned online.

## 3.3 Research approach

Saunders et al. (2019) assert that selecting the appropriate research approach is crucial for effective research design and strategies. They categorize three primary approaches: Deduction, involving testing theories; Induction, deriving theories from observations; and Abduction, seeking the best explanation for phenomena. Each approach guides researchers in shaping their investigations and drawing meaningful conclusions.

In this research, the chosen approach is predominantly inductive, with a secondary incorporation of deductive elements, utilizing secondary data collected from social media comments on Twitter and Instagram. The primary focus is on deriving insights directly from the existing dataset, prioritizing the inductive method to explore and uncover patterns, sentiments, and emerging themes in UK retail customer sentiment within the grocery and fashion industries.

The inductive component involves a thorough examination of the secondary social media comments dataset. Through sentiment analysis and text mining, the study aims to identify unexplored factors influencing customer sentiment, leveraging the richness of the existing social media interactions. This approach allows for a bottom-up exploration of customer attitudes and perceptions, enabling the emergence of new insights and a nuanced understanding of the unique dynamics in the online space.

While the primary focus is on inductive reasoning, a secondary deductive element is incorporated. Existing theories and frameworks related to customer sentiment in retail are considered as reference points to guide the analysis and interpretation of inductively derived findings. This dual-method approach aims to strike a balance between exploring new ground and validating emerging insights against established knowledge, ensuring the robustness and applicability of the research findings.

By giving priority to the inductive approach and acknowledging the secondary nature of the data, the research aims to contribute fresh perspectives to the understanding of UK retail customer sentiment on social media. Through this mixed-methods strategy, the study seeks to provide a holistic and nuanced exploration, offering valuable insights for shaping effective marketing strategies in the grocery and fashion industries based on the sentiments expressed by customers on social media platforms.

## 3.4 Research Design and Strategy

This study employs a mixed methods research design integrating both qualitative and quantitative techniques for a comprehensive analysis of social media data. Qualitative coding of a sample of tweets and Instagram comments is conducted to identify emergent themes related to customer sentiment. Quantitatively, sentiment analysis is undertaken leveraging machine learning algorithms to classify larger volumes of comments as positive, negative or neutral. By synergizing these approaches, a rich, multi-dimensional understanding of customer attitudes and experiences is achieved.

The overarching strategy is an inductive analysis focused on unpacking embedded perceptions within retail customer social media discourse to unveil unexplored factors shaping online sentiment. Deductive reasoning is secondarily incorporated by considering existing academic models of customer sentiment analysis to guide interpretative analysis. This mixed inductive-deductive approach enables new discoveries while retaining grounding in established theory.

## 3.5 Data Collection

The dataset comprises natural social media comments from 1000 customers each, spanning top-tier grocery and fashion brands within the UK market. This inclusive dataset encompasses conversations extracted from two pivotal social media platforms. Twitter data is sourced by directly scraping comments from brand profiles utilizing Python scripting, ensuring a direct and comprehensive collection method. Additionally, Instagram data is acquired through the use of IG Comment Exporter(Third party tool), enabling a robust compilation of user comments and interactions from this visual-centric platform.

The deliberate inclusion of both Twitter and Instagram guarantees a holistic coverage across diverse customer segments and their interactions with the brands. Among the ten companies included in this dataset—five from the grocery sector including Morrisons, Sainsbury, Tesco, Asda, and Aldi, and five from the fashion segment including Next, Jd sports, Primark, Sportsdirect.com, and Marks and Spencer—are prominent names within the respective industries. The grocery segment encompasses leading brands recognized for their presence and influence within the UK's grocery retail landscape, while the fashion segment includes influential names celebrated for their impact and prominence in the fashion market of the region.

## 3.6 Data analysis techniques

A mixed methods approach was utilized combining both quantitative sentiment scoring (sentimental analysis) and qualitative textual analysis (Text mining) for a comprehensive examination of the social media dataset.

First, to quantify prevailing sentiment trends, the entire corpus of retail brand posts underwent automated sentiment classification through Azure Machine Learning. The sophisticated neural network algorithms systematically assessed each text excerpt on a precise 0-100% sentiment polarity scale. This enabled granular quantification of positive, neutral and negative distributions across brands and platforms.

Second, to interpret the themes and language within the sentiments, a balanced stratified sample of posts per brand underwent manual linguistic analysis using Voyant Tools. By examining word frequencies, correlations and contexts associated with positive, neutral and negative subsets, the research identified pivotal terms characterizing each sentiment polarity.

In summary, synergizing broad-based automated sentiment scoring with targeted qualitative textual analysis provided both quantifiable sentiment trend data and a nuanced interpretation of the cognitive frames underlying expressed opinions. This mixed methodology delivered a multi-dimensional understanding of customer perceptions across major UK retail brands by leveraging the efficiency of computational analysis with the richness of manual textual assessment.

Key steps in analysis are:

A) Collect relevant social media dataset (tweets, Instagram comments etc.)

B) Clean and preprocess data (remove duplicates, formatting etc.)

C) Branch into quantitative and qualitative analysis methods

Quantitative:

D) Use Azure ML algorithms to computationally score sentiment of each text excerpt on 0-100% scale

E) Statistically analyse sentiment polarity distributions

Qualitative:

F) Take a coded sample of posts across positive/neutral/negative sentiments

G) Identify key themes, words using Voyant Tools text analysis

H) Interpret underlying cognitive frames and contexts

I) Integrate quantitative distribution findings with qualitative explorations for a multi-dimensional holistic understanding

## 3.7 Data Types

The collected dataset for this research comprises qualitative secondary data extracted from social media platforms, specifically Twitter and Instagram. The nature of the data encompasses user-generated comments, representing diverse opinions, perceptions, and sentiments expressed by customers interacting with top-tier grocery and fashion brands within the UK market. These comments form the qualitative backbone of the study, offering rich insights into the nuanced perspectives and subjective viewpoints of customers regarding their experiences with these retail brands. The qualitative nature of the data allows for a deep exploration of language nuances, sentiment analysis, and emergent themes through qualitative coding and linguistic examination, enabling a comprehensive understanding of customer sentiment within the retail landscape.

## 3.8 Data Cleansing Steps

The dataset, comprising user-generated comments extracted from Instagram and Twitter, forms the foundation of this research. After meticulous extraction from these social media platforms, the dataset was curated and organized within Excel for initial preprocessing. The initial steps involved importing the collected comments into Excel spreadsheets for initial assessment and preparatory measures. Leveraging Excel's functionalities, the data underwent preliminary cleansing processes, including the removal of extraneous elements such as emojis, URLs, and duplicates. Additionally, Excel facilitated basic formatting adjustments and initial categorization, laying the groundwork for subsequent detailed data cleansing and analysis procedures. Through Excel's interface, the data underwent initial standardization efforts to ensure consistency in language and format across the diverse array of comments gathered from these dynamic platforms. This initial phase within Excel served as a preliminary stage, preparing the dataset for more intricate data cleansing and analysis steps, ensuring that the subsequent analytical processes were executed on a well-organized and refined dataset. The ease of use and flexibility offered by Excel aided in the initial stages of data preparation, setting the stage for comprehensive cleansing and analysis to derive insightful perspectives on customer sentiments within the realm of retail interactions on social media platforms.

## 3.9 Ethical issues faced by the data.

Employing Twitter and Instagram data for sentiment analysis introduced ethical complexities. Obtaining user consent for extracting user-generated content proved challenging due to the absence of explicit permissions. Maintaining user anonymity during data extraction and analysis was pivotal to prevent inadvertent identification. Addressing inherent biases in social media content and extraction methods was essential for analysis accuracy and fairness. Transparency was paramount, necessitating clear outlines of methodologies, tools used, and research intentions, ensuring responsible data usage. Ethical hurdles encompassed consent acquisition, safeguarding user privacy, mitigating biases, and maintaining transparency—critical considerations in conducting ethical sentiment analysis with Twitter and Instagram data for academic research. Striking a balance between ethical data usage and extracting valuable insights from social media required careful navigation of these multifaceted ethical challenges.

## 3.7 Research Questions

a) How can social media analytics be utilized to understand UK retail customer sentiment?

b) What insights can be gained from social media analytics to inform marketing strategies for UK retailers?

c) How effective are social media analytics in improving marketing strategies and performance for UK retailers?

## 3.8 Research Objectives

* To analyse social media data from major platforms, especially Twitter (X) and Instagram, to identify key themes, trends, and insights into UK retail customer sentiment.
* To explore the use of various social media analytics techniques like text analytics, natural language processing, and sentiment analysis for analysing UK retail customer sentiment.
* To critically evaluate the challenges faced by UK retail brands through social media analytics for gaining actionable customer and marketing insights.
* To critically review existing academic literature on utilizing social media analytics to understand customer sentiment and inform marketing strategies.

## 3.9 Justification of Methodological Approach

This research uses an interpretivist approach combining qualitative coding and quantitative sentiment analysis to understand the nuanced perceptions underlying customer sentiments about retail brands on social media. It goes beyond basic sentiment polarity scores to uncover the subjective attitudes, motivations, and connections forming the basis of online opinions. By synergizing human interpretive analysis with computational efficiency, it aims to comprehensively comprehend subjective viewpoints constructed through social discourse. The methodology provides nuanced insight into customer perceptions to aid data-driven retail marketing decisions. Overall, it is carefully tailored to delve into the intricacies moulding socially constructed commentary to support strategic decision-making around customer sentiments.

# 4. Findings and Analysis

In this chapter, we delve into the sentiments expressed in social media comments for five leading UK retailers each in the grocery and fashion industries. Leveraging sentiment analysis and text mining, we aim to unveil nuanced consumer perspectives, identify prevalent themes, and derive actionable insights to inform strategic decisions within these dynamic market sectors.

## 4.1 Sentimental analysis

Sentiment analysis, or opinion mining, is a vital aspect of social media analytics. It involves systematically extracting and studying emotions and subjective information from text through natural language processing. This technique enables organizations to assess overall sentiment in online interactions, providing valuable insights into public perceptions of products, brands, or services (Liu, 2022).

Sentiment analysis using Azure Machine Learning is a popular natural language processing technique. It entails determining a text's sentiment, which might be valuable for social media analytics (Harfoushi et al., 2018).

### 4.1.1 Sentiment Analysis in UK Fashion Retail

The task involves conducting sentiment analysis on social media comments gathered for five prominent UK fashion industry companies: Next, JD Sports, Primark, Marks & Spencer, and SportsDirect.com using azure machine learning.

#### 4.1.1.1 Next's Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **266** | **17.06%** |
| Neutral | **101** | **52.43%** |
| Positive | **633** | **77.04%** |
| Grant Total | **1000** | **58.60%** |

Table Next’s Sentimental analysis

Table 1 depicts the sentimental scores of the company Next. Out of 1000 social media comments analysed from the company, the majority or 633 were positive, with an average positive sentiment score of 77.04%. 101 comments were neutral with an average neutral score of 52.43%, while the remaining 266 comments were negative, with a low average negative score of 17.06%. In summary, most of the comments had a favourable sentiment, averaging 58.60% out of 100%. Only a small portion were unfavourable, indicating that social media commentary regarding this company leans positive.

#### 4.1.1.2 JD Sports' Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **344** | **14.0%** |
| Neutral | **74** | **53.5%** |
| Positive | **582** | **79.1%** |
| Grant Total | **1000** | **54.8%** |

Table JD Sport's Sentimental analysis

Table 2 shows the sentimental scores of the company JD sports. Out of 1000 social media comments analysed from the company, the majority or 582 were positive, with an average positive sentiment score of 79.1%. 74 comments were neutral with an average neutral score of 53.5%, while the remaining 344 comments were negative, with a low average negative score of 14.0%. In summary, most of the comments had a favourable sentiment, averaging 54.8% out of 100%. Only a small portion were unfavourable, indicating that social media commentary regarding this company leans positive.

#### 4.1.1.3 Primark's Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **422** | **12.3%** |
| Neutral | **70** | **52.2%** |
| Positive | **508** | **80.7%** |
| Grant Total | **1000** | **49.8%** |

Table Primark's Sentimental analysis

Table 3 depicts the sentimental scores of the company Primark. Primark's sentiment analysis of 1000 comments showcase a predominantly positive reception with 508 comments reflecting positivity, averaging an impressive score of 80.7%. However, 70 comments were neutral, scoring 52.2%, while a lower count of 422 comments leaned negative, with an average score of 12.3%. Despite the mix, Primark maintains an overall positive sentiment score of 49.8%, highlighting a majority of positive sentiments with some neutral and negative feedback.

#### 4.1.1.4 Marks & Spencer's Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **604** | **8.2%** |
| Neutral | **59** | **53.9%** |
| Positive | **337** | **79.5%** |
| Grant Total | **1000** | **34.9%** |

Table Mark and Spencer Sentimental analysis

Table 4 shows the sentimental scores of the company Mark and Spencer. The sentiment analysis of Mark and Spencer's social media comments reveals varying perceptions. Among 1000 comments analysed, 337 were positive, averaging a high score of 79.5%, while 59 were neutral, scoring 53.9%. Surprisingly, 604 comments were negative, reflecting an average score of only 8.2%. The collective sentiment score for the brand stands at 34.9%, signalling a mix of positive and neutral comments overshadowed by a significant volume of negative sentiments.

#### 4.1.1.5 Sportsdirect.com's Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **574** | **10.1%** |
| Neutral | **64** | **53.9%** |
| Positive | **362** | **79.4%** |
| Grant Total | **1000** | **38.0%** |

Table Sport direct.com Sentimental analysis

The sentiment analysis of Sportsdirect.com's 1000 comments from table indicates a blend of reactions. Among these, 362 comments reflected positivity, scoring an average of 79.4%, while 64 comments maintained a neutral tone with a score of 53.9%. Surprisingly, a substantial count of 574 comments expressed negativity, averaging a score of only 10.1%. This results in an overall sentiment score of 38.0%, showcasing a mix of positive and neutral feedback overshadowed by a significant volume of negative sentiments towards sportsdirect.com.

#### 4.1.1.6 Comparative Analysis of Fashion Brands' Sentiments

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Brand | Social media comments collected | Positive | Neutral | Negative |
| Next | 1000 | 633 | 101 | 266 |
| JD Sports | 1000 | 582 | 74 | 344 |
| Primark | 1000 | 508 | 70 | 422 |
| Mark & Spencer | 1000 | 337 | 59 | 604 |
| Sports Direct.com | 1000 | 362 | 64 | 574 |

Table Comparative analysis of fashion brand’s sentiment

Table 6 illustrates the comparative analysis of the major fashion brands in UK. Analysing the sentiment scores across prominent fashion brands in the UK's social media landscape reveals intriguing insights. Among the brands surveyed, Next garnered 633 positive comments, 101 neutral, and 266 negatives out of 1000 total comments. JD Sports followed with 582 positive, 74 neutral, and 344 negative comments. Primark received 508 positive, 70 neutral, and 422 negative comments. Mark & Spencer had 337 positive, 59 neutral, and a notably high count of 604 negative comments. Finally, Sports Direct.com amassed 362 positive, 64 neutral, and 574 negative comments.

This data underscores a diverse spectrum of sentiments. While Next and JD Sports received more positive feedback than negative, Primark encountered a balance between positive and negative sentiments, with a significant volume of negative responses. Mark & Spencer faced a substantial amount of negative commentary, overshadowing their positive and neutral feedback. Sports Direct.com also contended with a notably high count of negative comments, affecting its overall sentiment score.

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Figure 6 Comparative analysis of fashion brands sentiment

Overall, this data signifies the nuanced perceptions within the fashion industry. It emphasizes the significance of online reputation management, highlighting the varying degrees of positivity, neutrality, and negativity that brands navigate in the dynamic realm of social media. Understanding and addressing these sentiments can profoundly impact a brand's image and customer relations in the competitive fashion market of the UK.

### 4.1.2 Sentiment Analysis in UK Grocery Retail

The task involves conducting sentiment analysis on social media comments gathered for five prominent UK grocery industry companies: Morrisons, Asda, Sainsbury’s, Tesco and Aldi using azure machine learning.

#### 4.1.2.1 Morrisons' Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **762** | **5.3%** |
| Neutral | **86** | **54.3%** |
| Positive | **152** | **79.8%** |
| Grant Total | **1000** | **20.8%** |

Table Morrison’s Sentimental analysis

Table 7 depicts the sentimental scores of the company Morrisons. Analysing sentiment from 1000 comments about Morrisons portrays a mixed landscape. Impressively, 152 comments were positively received, scoring an average of 79.8%. However, a significant 762 comments reflected negativity, averaging just 5.3%. Additionally, 86 tweets remained neutral, scoring an average of 54.3%. Overall, Morrisons' sentiment score stands at 20.8%, signalling a predominantly negative sentiment with scattered pockets of neutral and positive feedback.

#### 4.1.2.2 Asda's Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **547** | **10.0%** |
| Neutral | **94** | **53.2%** |
| Positive | **359** | **80.7%** |
| Grant Total | **1000** | **39.5%** |

Table Asda's Sentimental analysis

Asda's sentiment analysis from 1000 comments shown in the table 8 unveils a diverse spectrum. Impressively, 359 comments were positive, boasting an average score of 80.7%. However, a majority of 547 comments leaned negative, averaging 10.0%. Additionally, 94 comments maintained a neutral stance with an average score of 53.2%. Consequently, Asda's overall sentiment score stands at 39.5%, indicating a mix of predominantly negative sentiments overshadowing scattered neutral and positive feedback.

#### 4.1.2.3 Sainsbury’s Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **705** | **8.3%** |
| Neutral | **55** | **53.3%** |
| Positive | **240** | **78.7%** |
| Grant Total | **1000** | **27.7%** |

Table Sainsbury’s Sentimental analysis

Sainsbury's analysis from 1000 comments shown in the table 9 presents a mixed sentiment landscape. Impressively, 240 tweets were positive, averaging a score of 78.7%. However, a substantial 705 comments conveyed negativity, averaging only 8.3%. Additionally, 55 comments maintained a neutral stance with an average score of 53.3%. Overall, Sainsbury's garnered a sentiment score of 27.7%, signalling predominantly negative sentiments, though with notable pockets of neutral and positive feedback amidst the social media conversation.

#### 4.1.2.4 Aldi's Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **677** | **9.0%** |
| Neutral | **58** | **53.4%** |
| Positive | **265** | **81.7%** |
| Grant Total | **1000** | **30.9%** |

Table Aldi’s Sentimental analysis

Sentimental score of Aldi’s social media comments which is shown in table 10 showcases a diverse range of reactions. Notably, 265 comments exuded positivity, boasting an impressive 81.7% average score. However, a substantial count of 677 comments expressed negativity, averaging at 9.0%. Moreover, 58 comments remained neutral, scoring at 53.4%. Despite scattered pockets of neutral and positive feedback, Aldi's overall sentiment score stands at 30.9%, predominantly reflecting negative sentiments within the discussions surrounding the company's image.

#### 4.1.2.5 Tesco's Sentiment Analysis

|  |  |  |
| --- | --- | --- |
| Sentiment | Social Media Comments | Average Of Score |
| Negative | **632** | **9.4%** |
| Neutral | **80** | **53.0%** |
| Positive | **288** | **81.2%** |
| Grant Total | **1000** | **33.6%** |

Table Tesco's Sentimental analysis

In the realm of Tesco's social media portrayal from 1000 comments depicted in the table 11, 288 reflect positivity, averaging an impressive 81.2%. However, a significant count of 632 comments conveyed negativity, averaging at 9.4%. Moreover, 80 comments remained neutral, scoring at 53.0% average score. Overall, Tesco's sentiment score rests at 33.6%, indicating a blend of predominantly negative sentiments, despite notable pockets of neutral and positive feedback scattered across the discussions about the company.

#### 4.1.2.6 Comparative Analysis of Grocery Chains Sentiments

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Brand | Social media comments collected | Positive | Neutral | Negative |
| Morrisons | 1000 | 152 | 86 | 762 |
| Asda | 1000 | 359 | 94 | 547 |
| Sainsbury’s | 1000 | 240 | 55 | 705 |
| Tesco | 1000 | 288 | 80 | 632 |
| Aldi | 1000 | 265 | 58 | 677 |

Table Comparative analysis of Grocery Chains Sentiments

Table 12 depicts the comparative analysis of grocery chains sentiments of the social media in UK. The social media sentiment for the top UK grocery chains skews negative, indicating customer dissatisfaction overall in the retail food market. Morrisons generates the most negative chatter with 76.2% of comments being critical. Not far behind is Sainsbury's at 70.5%. While Tesco, Aldi and Asda also have majority negative feedback on social platforms, their numbers are lower ranging from 54.7% to 67.7%. The high amount of negative commentary for these household name brands suggests that British customers feel their experiences at major supermarkets consistently fall short of expectations. All the chains could benefit from targeted social engagement and public relations campaigns to start shifting sentiment in the other direction.

A graph of multiple colored bars

Description automatically generated with medium confidence

Figure 7 Comparative analysis of grocery chains sentiments

On the positive side, Asda tops the list with 35.9% positive social sentiment compared to the 15-25% range for the other four grocery retailers. So, while the prevailing social sentiment for UK food chains is negative, Asda is moving the needle more favourably amongst its customer base. The percentage of neutral comments also shows a small bright spot for the industry. Neutral statements make up 5-9% of remarks, indicating some satisfaction if not outright enthusiasm for grocery offerings. This cloud of neutrality represents an opportunity for brands like Tesco, Aldi, Sainsbury's and Morrisons. By addressing pain points surfaced in the negative commentary, they might ultimately convert more passive shoppers into vocal brand advocates.

### 4.1.3 Overall Findings from Sentiment Analysis in UK Retail

The sentiment analysis on major UK fashion and grocery retailers reveals an overwhelmingly negative perception on social media. For fashion brands like Mark & Spencer and SportsDirect.com, over 60% of comments were critical - a damaging result in the realm of online reputation. Grocery sentiment followed suit with largely negative feedback. Major chains like Tesco, Aldi and Sainsbury's dealt with 63-70% negative remarks. Only Asda fared slightly better at 55%.

This negative skew exposes significant dissatisfaction amongst British consumers when interacting with prominent high street and supermarket brands. While some retailers like Next and JD Sports maintained small positive sentiment leads, the broader market commentary conveys deep frustrations with the state of shopping across sectors.

For retail brands, this signals urgent need for reputation and experience fix across channels. Targeting pain points called out in social commentary can help grocery chains like Tesco boost sentiment from abysmal 10% levels. Fashion retailers must also re-inspire customers. Strategic investments in omni-channel experience, ethics and sustainability can help reverse the tides of negativity - especially for brands like Mark & Spencer now struggling with only 34% positive feedback.

## 4.2 Text mining

As mentioned earlier text mining is the extraction of meaningful information from unstructured text using algorithms. It efficiently analyses large volumes of text, unveiling valuable patterns and trends. This process enhances the speed of information retrieval, making it easier to extract useful insights from extensive textual data sets, thereby aiding in knowledge discovery and decision-making (Ajay Jadhav et al., 2023).

Voyant Tools is an open source text analysis application used in text mining. It facilitates in finding prominent fields of inquiry through quantitative methodologies and disclosing main discourse themes through distant reading and interactive reading capabilities (Kairaitytė-Užupė et al., 2023).

### 4.2.1 Application of Text Mining in Fashion Industry Analysis

To gain insights from positive and negative comments in the UK fashion industry, comments from each company are filtered using MS Excel and analysed using the voyant tool.

#### 4.2.1.1 Insights from text mining on the positive comments of the fashion retail industry

**A close up of words

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Figure 8 Cirrus based on positive comments.

Figure 8 depicts the cirrus diagram obtained from the voyant tool. The prominent terms in this word cloud, extracted from the Voyant tool, unveil a positive sentiment surrounding the UK retail fashion industry. Among the recurring words, 'service,' 'great,' 'delivery,' and 'staff' stand out, indicative of the customers satisfaction. The prevalence of 'service' implies a strong emphasis on customer care, suggesting an attentive and helpful approach by the retail outlets. 'Great' and 'delivery' emphasize the overall positive experience, implying that customers are content not only with the products but also with the timely and efficient receipt of their orders.

The term 'staff' further reinforces the positive ambiance, suggesting a friendly and supportive team contributing to a pleasant shopping atmosphere. The positive sentiments are also echoed in words like 'love,' 'happy,' 'excellent,' and 'thank,' indicating genuine appreciation from customers. Additionally, the mention of 'prices' suggests that customers find the cost reasonable, contributing to their satisfaction. Overall, this word cloud paints a picture of a retail fashion industry that excels in providing excellent service, quality products, and a positive shopping experience, fostering customer loyalty and contentment.

**A diagram of a service

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Figure Positive linking words - Service

Figure 9 depicts the words that are linked to the word service on the basis of positive comments. In the UK fashion retail sector, positive words linked to "service" depict commendable customer experiences. "Happy," "good," "great," "quick," "fast," and "excellent" highlight customer satisfaction. Emphasizing "delivery," "received," and "easy" reflects efficient, reliable product arrival—an essential factor meeting customer expectations. "Quality product" underscores commitment to superior merchandise. These positive associations within "service" signify a customer-centric approach valuing promptness, reliability, and quality. This approach ensures a seamless experience, from order to receipt, fostering brand loyalty. This focus on service excellence enhances customer satisfaction and word-of-mouth, crucial in the competitive UK fashion retail landscape.

**A diagram of a staff

Description automatically generated**

Figure 10 Positive linking words - Staff

Figure 10 depicts the positive words linked to "staff" in the UK fashion industry showcase a customer-centric ethos. Traits like "friendly," "polite," "helpful," and "good" signify a team focused on fostering a welcoming environment, crucial in retail. The mention of "talking" hints at effective communication, enhancing engagement and product understanding. Emphasizing "service" underscores commitment to excellent customer care, influencing customer perceptions and fostering loyalty. In the competitive fashion landscape, these traits build rapport and trust. Creating an environment where customers feel valued by courteous staff contributes significantly to positive brand image and loyalty in the UK fashion industry's customer-centric approach.

#### 4.2.1.2 Insights from the text mining on the negative comments of the fashion retail industry

**A close-up of words

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Figure 11 Cirrus based on negative comments.

Figure 11 depicts the negative feedback from UK fashion retail customers centres on issues: product quality, sizing inconsistencies, and refund needs. Dissatisfaction with delayed deliveries and poor service, evidenced by "delay," "poor service," and "email," reveals communication and support inadequacies. "Ordered," "days," and "just" indicate frustration due to prolonged wait times for resolution. Criticism around "staff" suggests ineffective support. These concerns encompass quality, delivery delays, communication inefficiencies, and unsatisfactory service. To improve, consistency in products, streamlined delivery, responsive communication, and enhanced service interactions are imperative. Addressing these concerns is pivotal to bolster customer satisfaction and loyalty in this fiercely competitive UK fashion retail landscape.

**A diagram of a service

Description automatically generated**

Figure 12 Negative linking words - service

Figure 12 depicts the negative linking words associated with the term service. These negative comments linked to "service" in the UK fashion industry highlight significant dissatisfaction among customers. "Refunded," "weeks," "poor," "terrible," and "unhappy" indicate prolonged refund processes, likely causing frustration and dissatisfaction. The mention of "online" suggests that these issues predominantly arise from online shopping experiences, where customers face challenges with service quality, leading to disappointment and unhappiness. The convergence of these negative descriptors around "service" signifies a critical need for improvements in online customer service standards, quicker resolution of refund-related concerns, and overall enhancement of the customer experience to regain trust and satisfaction within the UK fashion retail sector.

4.2.2 Application of Text Mining in Grocery Industry Analysis

Comments from each company are filtered using MS Excel and then examined using the Voyant tool to gather insights from both positive and negative comments in the UK fashion industry.

#### 4.2.2.1 Insights from Positive Text Mining in Grocery Retail

**A close up of words

Description automatically generated**

Figure 13 Cirrus based on positive comments.

The figure 13 shows the positive comments circling around the UK grocery industry highlight customers' satisfaction with various aspects. "Good," "great," "friendly," "helpful," and "excellent service" reflect a positive experience with staff, indicating helpful and friendly interactions. "Prices" and "delivery time" suggest satisfaction with affordability and timely delivery services. Mentions of "products," "store," and "items" signify contentment with the range and quality of available products. The inclusion of "customer" suggests a focus on customer-centric services. Overall, these positive descriptors emphasize a well-rounded positive shopping experience, ranging from product variety and quality to excellent service and customer-oriented approaches within the UK grocery industry.

**A diagram of a good product

Description automatically generated**

Figure 14 Positive linking words - Good

The positive comments revolving around "good" in the UK grocery retail industry is shown in the figure 14. It signifies a comprehensive appreciation for various aspects. "Value," "prices," and "great quality shopping" indicate customers' satisfaction with the balance between affordability and product excellence. "Delivery" suggests contentment with timely and reliable service. Mentions of "products" and "food" reflect satisfaction with the quality and variety available. The inclusion of "service" emphasizes a positive customer experience, highlighting attentive and efficient assistance. Overall, these positive descriptors surrounding "good" depict a holistic endorsement of excellent value, quality products, fair pricing, reliable delivery, and commendable customer service within the UK grocery retail landscape.

**A diagram of service

Description automatically generated**

Figure 15 Positive linking words - Service

Figure 15 illustrates that positive comments encircling 'service' in the UK retail grocery industry portray a comprehensive satisfaction with various elements. 'Excellent,' 'great,' and 'staff' indicate exceptional service quality, highlighting helpful and attentive staff members. Mentions of 'delivery' and 'time' suggest efficiency in timely deliveries, meeting customer expectations. 'Products' and 'shop' signify a positive shopping experience, likely attributed to well-stocked and diverse product offerings. Overall, these positive descriptors surrounding the word 'service' illustrate a commendable customer-centric approach within the UK retail grocery sector, emphasizing efficient delivery, excellent staff support, and a satisfying shopping experience, contributing to customer loyalty and positive perceptions of the brand.

#### 4.2.2.2 Negative Text Mining Insights in Grocery Retail

**A close up of words

Description automatically generated**

Figure 16 Cirrus based on negative comments.

Figure 16 depicts the Customers negative feedback in the UK grocery industry. It centres on issues with refunds, delivery times, and online shopping. "Refund" and "told time" suggest dissatisfaction with communication or delays in refund processes. "Delivery," "days," and "order" highlight concerns about delayed deliveries impacting the shopping experience. Mention of "customer" and "service" implies dissatisfaction with overall customer service. These comments underscore grievances related to delays in refunds, prolonged delivery times, and unsatisfactory customer service, highlighting crucial areas requiring improvement within the UK grocery industry to enhance customer satisfaction and experience.

**A diagram of a delivery service

Description automatically generated**

Figure 17 Negative linking words – Order and Delivery

Figure 17 depicts the negative comments surrounding "delivery" in the UK grocery retail context depict dissatisfaction with various facets. "Service" linked to "driver" implies discontent with the conduct or efficiency of delivery personnel. "Order" associated with "items placed," "food," and "online" suggests issues related to the process of placing orders for grocery items online, possibly indicating discrepancies or dissatisfaction with the selection, accuracy, or quality of items ordered. Overall, these associations underline customer grievances related to delivery personnel, order accuracy, and the online ordering experience, highlighting critical areas requiring attention and improvement within the UK grocery retail delivery services.

# 5. Conclusions and Recommendations

## 5.1 Conclusions

This research set out to critically evaluate how major UK fashion and grocery retailers can effectively leverage social media analytics techniques to derive actionable insights from unstructured shopper sentiment data. The goal was informing data-driven marketing and merchandising decisions to enhance financial performance.

A mixed methods approach combining sentiment analysis and text mining of social data from Twitter and Instagram unveiled nuanced consumer perspectives. Analysis of 1000 comments per top grocery (Tesco, Sainsbury's, Aldi, Asda, Morrisons) and fashion (Next, JD Sports, Primark, sportsdirect.com, M&S) brands in the UK market revealed crucial themes and patterns shaping customer attitudes. Key findings confirm social listening offers invaluable intelligence, yet current retail strategies inadequately tap potential.

The main finding from the analysis is that big UK brands are facing a major problem on social media: most comments, about 60-70%, are complaints. This is a big concern because nowadays, a brand's reputation is super important in retail. For fashion retailers, people were unhappy about things like the quality of clothes, wrong sizes, trouble getting refunds, and late deliveries. Meanwhile, grocery stores got a lot of negative feedback about not communicating well, not having good customer support, and messing up orders. All this unhappiness shows that UK retailers aren't making people happy or meeting what they expect, no matter where they're talking about the brand. It's really important for them to make quick changes to win back people's trust and make them want to support and talk positively about the brand again.

Beyond pervasive negativity, the rich discourse within comments exposes specific pain points. In fashion, brands rely heavily on online channels where subpar service quality causes the most discontent regarding refund handling and communication lags. Key grocery grievances involve order/delivery accuracy and refund response times. Targeting these recurring issues presents opportunities to markedly improve sentiment. Platform distinctions also emerged, with Instagram feedback focused on style and self-identity aspects while Twitter comments centred on reputation and corporate social responsibility. Retailers must fine-tune engagement strategies accordingly.

While severe in tone, the uncover insights equip retailers with vital awareness to rehabilitate retention and lift lifetime value. Nearly all brands studied face customer-related threats, yet harnessing the discourse as competitive intelligence helps strategically transform criticism into solutions and social detractors into loyal advocates. Indeed, positive commentary emphasizes how staff attitude, merchandise quality and reliable fulfilment still foster satisfaction when executed well, signalling pathways for improvement. Ongoing social listening will be imperative to track brand health.

Ultimately these discoveries validate existing literature on the untapped potential within unsolicited social data to profoundly enhance customer and marketing strategy. When systematically mined using latest analytics, the voice of the customer exposed through online commentary delivers a real-time barometer into evolving attitudes, unmet wants and brand affinities unavailable through traditional channels.

5.2Recommendations5.2.1 Recommendations for UK Retail sectors

Based on the research conclusions, the following recommendations aim at addressing the urgent need and strategic opportunities to improve brand health, experience deficiencies and historically negative social sentiment currently diminishing UK retail performance across all the sectors.

**1.Implementing a 24/7 Social Listening Command Centre**

Create dedicated 24/7 social listening hubs for constant monitoring of brand discussions across Instagram, Twitter, reviews, and new platforms. Allocate resources for real-time community management, trend analysis, and crisis detection. These centres oversee operational issues, ensuring integrated consumer insights are promptly shared. The aim is continuous vigilance, maintaining awareness of branded conversations, and swiftly addressing emerging concerns. By committing to this, the focus remains on active engagement, trend spotting, and immediate responses, fostering a proactive approach to manage and distribute consumer insights seamlessly.

**2. Leveraging AI and NLP for Scalable Social Analytics**

Utilize advanced AI and NLP in social analytics for a revolutionary shift in processing unstructured text data. This transformation yields quantified sentiment metrics and in-depth customer insights, surpassing manual methods. The integration of AI and NLP systematically deciphers vast amounts of data, providing extensive emotion analysis and comprehensive customer perspectives. This next-generation approach enhances our understanding of customer sentiment and voice, offering a nuanced understanding that surpasses traditional monitoring techniques. The result is a scalable and profound insight mechanism that harnesses technology for comprehensive and contextual customer intelligence.

**3. Building an Analytics-Driven Executive Culture**

Nurture executive proficiency in utilizing social data analytics and intelligence by implementing educational programs, insights forums, customer advisory panels, and cultural initiatives. These efforts aim to instil a culture of data-driven decision-making, ensuring leaders grasp the significance of leveraging social data. Through educational programs, executives gain fluency in interpreting and applying insights gleaned from social analytics. Insights forums and advisory panels serve as platforms for exchanging perspectives and refining strategies based on informed data analysis. Ultimately, these concerted efforts cultivate a culture where data becomes integral to executive decision-making processes, fostering a deeper understanding and application of social data intelligence.

**4. Establishing Unified Social Media Governance**

Craft comprehensive strategies for social content, management protocols, and community engagement guidelines that harmonize enterprise and channel/product activities. These frameworks aim to maintain authenticity while fostering brand loyalty and safeguarding reputation. By defining clear content strategies, managing platforms effectively, and establishing engagement guidelines, the goal is to unify the brand's presence across various channels. The focus remains on nurturing genuine brand advocacy within communities while safeguarding the brand's integrity. This cohesive approach ensures consistency, authenticity, and a strong, loyal brand following while proactively managing and preserving the brand's reputation in the digital sphere.

**5. Enhancing Omni-Channel Experiences**

Allocate resources to specialized digital teams to integrate social, mobile, AI, and cloud technologies. Their focus is on enhancing the entire omni-channel process, from start to finish. By staying attuned to evolving customer preferences, these teams ensure products and services align with customer desires. The goal is to revolutionize the omni-channel experience, making it seamless and innovative with cutting-edge tech. This investment enables swift adaptation to changing needs, offering top-notch support and fostering ongoing innovation across channels, all while staying aligned with what customers want.

**6. Upholding Ethics and Privacy in Consumer Data Use**

Sustain a steadfast commitment to ethics, transparency, and privacy while harnessing consumer data to cultivate community trust and ensure the enduring viability of social initiatives. This emphasis guards against pitfalls exposed in recent controversies such as the ASOS worker review scandal. Upholding ethical standards in data utilization fosters transparency, nurturing trust within the community. Prioritizing privacy safeguards consumer interests and fortifies the foundation of social initiatives. By learning from past incidents, the focus remains on responsible data practices, steering clear of risks, and prioritizing integrity. This principled approach solidifies trust, fostering sustainable success in social endeavours while upholding ethical standards.

### 5.2.2 Recommendation for Fashion industry

The negative sentiment surrounding the UK fashion industry highlights critical areas for improvement. To address these concerns effectively, a multi-faceted approach is essential.

**1. Improve Product Quality and Sizing Consistency**

Implementing rigorous quality control checks, investing in automation, and expanding product sampling during fit and sizing trials can improve product quality and consistency, while providing detailed size and fit information can set clear customer expectations.

**2. Streamline Delivery Processes and Minimize Delays**

Implementing warehouse management, inventory tracking, and robust logistics partnerships can streamline order fulfilment, improve customer experience, and reduce delays through real-time monitoring.

**3. Revamp Online Customer Service**

Implementing chatbots and AI in self-service portals, training staff on empathy, and providing clear service level agreements can enhance customer support and improve responsiveness.

**4. Invest in Staff Training and Empowerment**

Implementing comprehensive onboarding and training programs for retail staff, focusing on soft and hard skills, manager shadowing, customer satisfaction metrics, and empowering staff to take ownership, enhances capabilities and motivation.

### 5.2.3 Recommendation for Grocery industry

To improve the negative sentiments plaguing the UK grocery industry, several key areas require immediate attention.

**1. Refine Refund Processes**

Automated refund approval workflows, service level agreements, and dedicated customer service staff can expedite procedures, manage expectations, and enhance transparency, while expanding eligibility criteria can provide customer flexibility.

**2. Enhance Delivery Efficiency**

Implementing GPS tracking, optimizing routes, and expanding fleets improves delivery timelines. Training programs ensure professional conduct, while notifications and contactless preferences enhance customer experience.

**3. Revamp Online Platform**

The online grocery store should have to be revamped with AI and ML for improved user experience, enhanced order fulfilment accuracy, expanded product categories, and cold storage for quality.

**4. Elevate Customer Service**

Omni-channel customer service, AI, and sentiment analysis, enables proactive issue resolution, staff training, call-back functionality, and personalized interactions to strengthen relationships and reduce effort.

**5. Implement Customer Feedback Loops**

Customer feedback through surveys, reviews, and advisory panels helps identify pain points, improve supply chain, and fosters trust, aiding in policy decisions and digital innovation efforts.

With appropriately resourced teams, governance and cultural readiness established through these proposals, UK retail brands gain capacity to transform mass criticism into targeted solutions. They equally cultivate environments where inspiration from positive commentary amplifies innovation and advocacy. Overall, embracing the abundance of contextual customer perspectives flowing through online social channels promises enhanced relevance, loyalty and performance - delivering substantial competitive advantage to digitally fluent UK retail organizations in the evolving omni-channel marketplace. The strategies presented aim to progress retailers from minimal listening towards embedded intelligence across the enterprise.

## 5.3 Limitation of the work

While this study gives useful insights into customer sentiment for big UK fashion and food firms on social media, it does have certain limitations. The analysis is limited to two industries and ten brands, limiting generalizability throughout retail. The sample of 1000 comments per brand, while significant, is simply a snapshot compared to a comprehensive corpus spanning years. Additional flaws emerge from relying primarily on Twitter and Instagram when customers engage across many networks. Nuanced perceptions from lengthy Trustpilot reviews are omitted. The emphasis on dominant sentiment scoring also ignores volume-based indicators. Tracking the volume of comments over time might reveal fluctuations in brand relevance. Rich profiling is further hampered by the absence of demographic information about commenting users. Variations between age groups and geographic areas are yet unclear. Lastly, the quick growth of social media means that results show sentiment momentarily rather than over time. Monitoring is necessary to identify changes as new problems and emergencies arise and as campaigns and inventions bring about new developments. To improve insights on changing retail brand health in the UK's dynamic digital world, future studies should address these constraints by including demographic dimensions, expanding data amounts and sources, incorporating various indicators, and encompassing more industries.

## 5.4 Future Prospects

This research unveils ample opportunities for additional exploration of social data analytics in UK retail. Further studies could expand the industry and brand scope beyond fashion and grocery to encompass other sectors. Increasing sample sizes over longer timeframes would enhance generalizability. Comparing sentiment fluctuations year-over-year using time series analysis promises deeper awareness of shifting attitudes. Integrating demographics could expose variances across ages, regions and genders. Widening the source diversity beyond the predominant platforms of Twitter and Instagram would reduce bias - inclusion of lengthy Trustpilot reviews may add nuance. While the current emphasis on dominance of positive or negative skews risks overlooking volume indicators, tracking the frequency of relevant keyword mentions over time could signal rising or declining interest/relevance. As social platforms and usage patterns continue evolving rapidly, persistent monitoring through listening centres will remain essential to promptly detect emergent crises. Overall, this research sets the stage for an exciting frontier of studies that harness analytics to translate unfiltered commentary into consumer insights for competitive advantage. Replicating the methodology across industries, brands and analytics techniques will enrich understanding of the factors shaping retail brand perceptions. As technology progresses, integrating next-generation AI and NLP promises unprecedented processing of complex social data at scale towards ever more contextualized and actionable intelligence.

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# 7. Appendix

## 7.1 Ethics Certificate

A certificate of ethical approval

Description automatically generated

Figure Certificate of ethical approval

## 7.2 Python Script

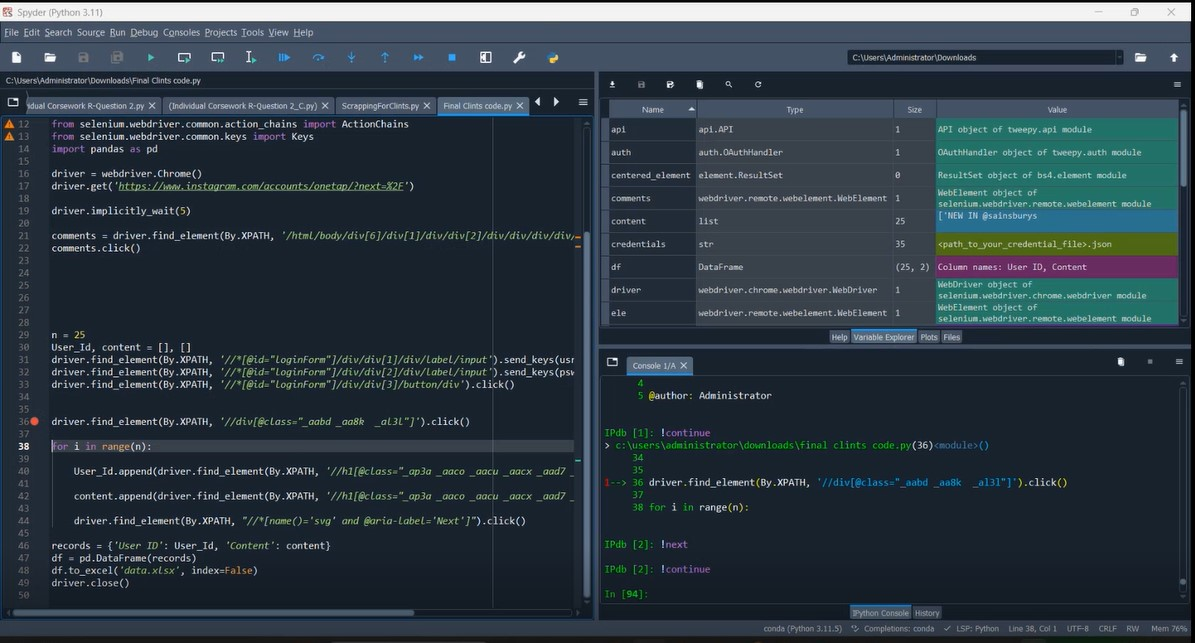


Figure Python Script

## 7.3 IGCommentsExport

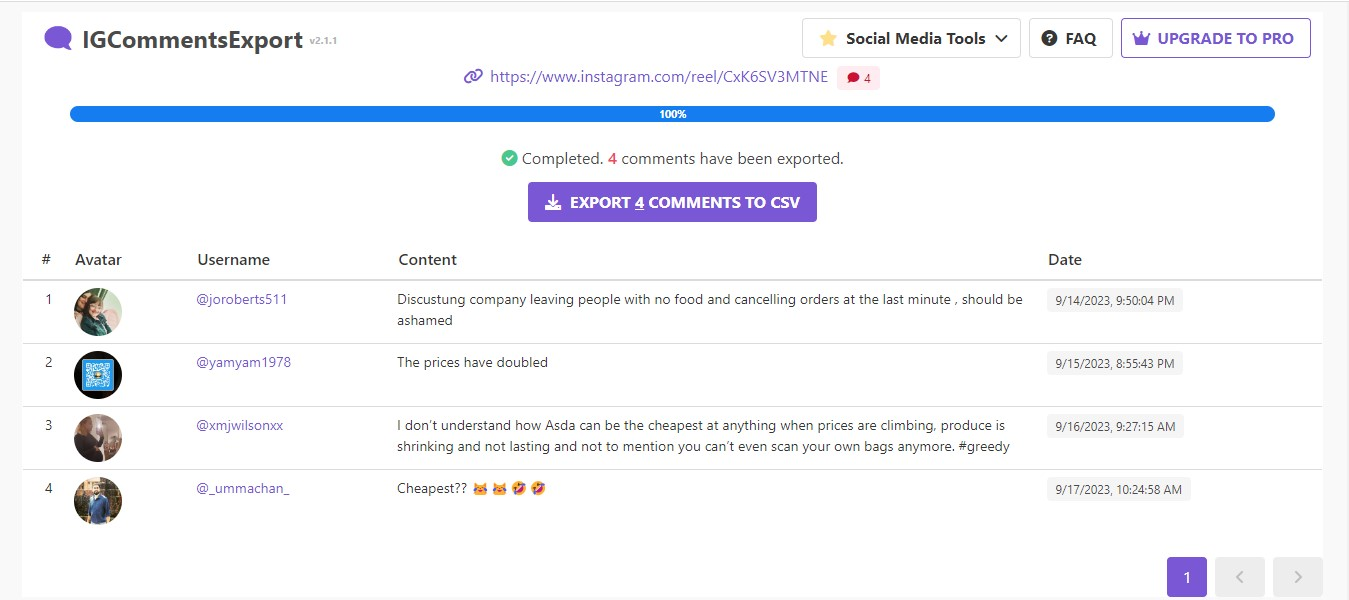


Figure IGComments Export