

Article

Utilising Artificial Intelligence to Turn Reviews into Business Enhancements through Sentiment Analysis

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Abstract: The use of sentiment analysis methodology has become crucial for e-commerce enterprises in order to optimise their marketing tactics. In the present setting, the authors strive to demonstrate the ethical and efficient use of artificial intelligence in the realm of business. The researchers used qualitative research methodologies to analyse a total of 1687 evaluations obtained from 85 online retailers associated with electronic commerce Europe Trustmark. These stores were linked with 18 different nations and operated over 14 distinct domains. The investigation used the combined power of natural language processing and machine learning, implemented via a Software-as-a-Service (SaaS) platform. The results of the study indicate that consumers often exhibit a neutral emotional tone while leaving one-star ratings. Although the influence of unfavourable evaluations is generally limited, it highlights the need for more attentiveness in their management. The extent to which users interact with goods and services has a substantial impact on the probability of publishing reviews, regardless of whether the encountered experience is unpleasant or favourable. The authors urge for the acquisition of tools and skills in order to boost the efficiency of managers and experts in parallel with expanding technological landscapes, with a particular emphasis on the utilisation of artificial intelligence for sentiment analysis.

Keywords: sentiment analysis; content analysis; reviews; artificial intelligence; Trustmark



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1. Introduction

The rise in artificial intelligence (AI) is undeniably reshaping various aspects of daily lives. Its impact on the human cognition and society is marked by a focus on problem-solving and critical thinking [1]. This development has also raised concerns about potential job displacement [2,3]. Within this context, researchers have delved into the effects AI has on different facets of human society, including the well-being of workers, changes in the nature of work and the anxiety associated with AI [4–6]. Nevertheless, it is worth noting that evidence supports the coexistence of AI and human workers in the workplace, as advocated by corporate perspectives [7]. The use of artificial intelligence (AI) techniques and technologies in business operations has the potential to enhance productivity at the organisational level [8]. From this particular standpoint, the existing research highlights the deficiency in the modelling of artificial intelligence (AI) utilisation [9], particularly within the realm of business [10–12].

Marketing, as a distinct field within the realm of business, is significantly impacted by the contentious use of artificial intelligence (AI). Research has shown the correlation between this technology and its implications in terms of ethical concerns [13] or commercial strategies. A compelling illustration of this assertion may be seen in the material produced with ChatGPT or other generative AI tools [14,15]. The use of artificial intelligence (AI) may provide various advantages across diverse domains [16,17].

In the realm of electronic commerce, the human-centric approach involves the creation and enhancement of digital purchasing experiences. The method necessitates the prioritisation of accommodating unique user preferences and habits [18–22]. Additionally, it acknowledges the need of establishing a user-centric environment that is especially tailored to meet the expectations and desires of consumers. In the realm of Industry 5.0, which encompasses the utilisation of technology to enhance customer experience, the adoption of a human-centred viewpoint yields significant insights for e-commerce enterprises. This approach contributes to the establishment of trust among clients, the improvement of overall user experience, and the promotion of company sustainability [23].

AI-powered technologies, including natural language processing (NLP) and machine learning (ML), are being increasingly used by corporations for marketing objectives, yielding significant beneficial outcomes. Sentiment analysis, also known as opinion mining, is a process that involves the use of natural language processing and machine learning techniques to automatically determine and evaluate the sentiment or emotion expressed in a piece of text. It helps in understanding whether the sentiment conveyed in the text is positive, negative, or neutral. The use of this technology is advantageous in enhancing client engagement, boosting sales, minimising expenses [24], and gaining a competitive edge “in an ever more data-focused and customer-oriented setting” [25]. The function of sentiment analysis plays a crucial part in managing decision-making processes pertaining to artificial intelligence. The approach of gathering and evaluating contextual data on the Internet, as represented by [26], has a substantial influence on company growth. The use of review analysis may assist managers in enhancing their goods and services, resulting in favourable long-term implications [27].

The objective of this research is to showcase the use of AI in performing sentiment analysis. The purpose is to obtain insights into the emotions expressed by people in their search engine evaluations, with the ultimate goal of developing business strategies that prioritises the needs and preferences of individuals. In order to achieve this objective, the researchers used NLP, a subfield of AI to comprehend the language used by the users. The primary goal was to address three specific research inquiries:

- How can individuals with unpleasant emotions express their opinions in written reviews?
- What impact do unfavourable ratings have on the most relevant reviews?
- What is the subject matter of the reviews?

In relation to the aforementioned inquiries, three specific goals were formulated: The objectives of this study are as follows: (O1) to gain insight into the reviewing patterns shown by users expressing unfavourable sentiments; (O2) to ascertain the influence of bad reviews; and (O3) to determine the subject matter of the reviews.

The use of sentiment analysis within the realm of internet commerce has several benefits. The aforementioned factors include the prospective outcomes of implementing this strategy, including but not limited to: a rise in sales figures, an enhancement in customer satisfaction levels, an improvement in the quality of customer service, a possible decrease in customer attrition rates, and an amplification of brand awareness. Upon performing an extensive literature study, the authors identified and proposed three hypotheses. Initially, it is noteworthy that a bad review has the potential to have a favourable impact on a user's subsequent activities. This suggests that persons who have had a poor experience are more likely to express their opinions by leaving a review, in contrast to those who have had a pleasant interaction. Furthermore, in formulating each hypothesis, the authors employed the term “positively impacts” to highlight that a certain component or condition leads to a beneficial or desirable consequence pertaining to user behaviour and their interaction with reviews and experiences.

Hypothesis 1. *Adverse emotions positively impact the users' inclination to articulate their unfavourable encounters via writing.*

This theory posits that in instances when users experience unpleasant emotions, possibly as a result of a subpar encounter, it motivates them to engage in proactive behaviour by articulating their discontentment via written feedback. In this instance, the term “positive impact” pertains to the notion that adverse emotions prompt users to provide comprehensive feedback on their unfavourable encounter, hence yielding the desired effect.

Hypothesis 2. *The prominence of reviews as the most relevant information is positively impacted by the presence of a comprehensive account of a bad experience.*

This hypothesis posits that the probability of a user’s review being deemed extremely relevant and prominently displayed is heightened when they articulate a bad experience in a comprehensive manner. The phrase “positively impacted” denotes that a comprehensive unfavourable encounter had a beneficial effect on the perceived significance of a review.

Hypothesis 3. *The engagement of users with goods and services has a positive impact on the likelihood of publishing a review, irrespective of whether the encounter is characterised by a bad or pleasant experience.*

The present hypothesis posits that user engagement with goods or services is positively associated with a higher probability of leaving a review, irrespective of the valence of their experience. In the present context, the phrase “positively impacts” denotes that engaging with the product or service increases the probability of a user performing the action of submitting a review.

The present situation of the research area is explicated in the following four subsections. The literature review highlights the user-centric approach to electronic commerce, emphasising the importance of understanding the demanding needs of consumers and the need of considering them for future improvements. The following section delves into the analysis of search engine evaluations published by Business Profile (BP), with specific emphasis on the crucial significance of trust and trademark within the realm of internet commerce. The last component of the literature study makes a connection between sentiment analysis and internet commerce. The authors developed three hypotheses based on the findings of the literature review. These hypotheses are consistent with the stated aims and research inquiries. The following section outlines the methodology used in the study. The study’s results enabled the formulation of innovative tactics as suggestions that have consequences for both management and academic contexts. Moreover, the study admits its inherent constraints and proposes potential directions for further investigation in the conclusion segment.

2. Literature Review

The literature indicates that sentiment analysis has significant potential as a beneficial instrument for e-commerce enterprises. The use of sentiment analysis enables organisations to obtain vital data about client sentiment, detect new trends, enhance goods and marketing strategies, and personalise the shopping experience.

In general, the studies indicate that Google reviews have significant potential as a beneficial instrument for e-commerce enterprises. Businesses may enhance their trust, search engine optimisation (SEO), and customer service. The general reputation is actively encouraging contented customers to provide good evaluations and swiftly and carefully address all reviews received. Also, the use of trademark is consistent with the principles of a holistic branding strategy. Trust extends beyond individual items and embraces the whole of the brand experience. The cultivation of market distinction is a crucial aspect in highly competitive e-commerce environments, where trademarks play a significant role in establishing a unique market presence. The act of differentiating oneself in this manner enhances trust via the projection of a professional and distinctive image [28].

2.1. The Humancentric Perspective on Electronic Commerce

With the use of sophisticated data analytics and machine learning algorithms, e-commerce platforms can obtain valuable insights into the behavioural patterns and preferences of users. The data are then used to provide tailored suggestions for items, content, and marketing approaches. This practice enhances the user experience by providing relevant offers, leading to increased user engagement and conversion rates [29]. The inclusion of Google reviews plays a substantial role in enhancing the trustworthiness of an e-commerce firm. The brand's goods and services are imbued with a feeling of confidence due to the positive emotions expressed by previous consumers [30].

The integration of consumer evaluations and ratings provides valuable information to prospective buyers, hence validating their purchasing decisions. The trustworthiness of items and the buying experience is enhanced using social validation methods such as reviews, testimonials, and user-generated material [31].

The presence of a complex or lengthy checkout procedure has the potential to lead to instances of abandoned shopping carts, but the use of a humancentric approach optimises the checkout process by reducing the number of stages involved and delivering a smooth experience. The provision of many channels for customer support, including live chat, email, and phone, together with the timely and efficient handling of enquiries, enhances the overall user experience. Effective and transparent communication on the status of orders and updates on delivery serves to enhance customer satisfaction [22].

The incorporation of accessibility considerations in the design and development of the e-commerce platform is crucial in upholding a humancentric approach, particularly for users with impairments. This includes functionalities such as screen readers, navigation that is compatible with keyboards, and descriptive text for photos [32].

The integration of sustainability practices and ethical considerations inside e-commerce platforms has garnered significant attention from conscientious consumers, mostly driven by growing environmental concerns. The incorporation of ethical practices in the areas of sourcing, manufacturing, and supply chain management is also seen as a significant factor in cultivating a favourable brand image [33]. In conclusion, when used in the context of electronic commerce, humancentric design may be leveraged to enhance the user experience via several means. One illustrative use of this is its utilisation in various contexts.

Firstly, the personalisation of the shopping experience may be achieved by e-commerce enterprises via the use of user data to comprehend their interests and preferences. This enables the businesses to provide personalised recommendations, discounts, and targeted marketing messages to enhance the overall shopping experience.

Secondly, to enhance the comfort of the checkout process, e-commerce enterprises may implement measures to streamline the procedure and facilitate the input of payment and shipping details. This optimisation can effectively mitigate instances of abandoned carts and thus bolster sales.

Therefore, for achieving exceptional customer service: e-commerce enterprises may cultivate trust and foster customer loyalty by offering several avenues for customer assistance and promptly addressing queries with efficiency.

Finally, the development of a sustainable and ethically driven electronic commerce platform: by integrating sustainable practices and ethical concerns into their operational strategies, e-commerce enterprises have the potential to attract conscientious customers and foster a favourable brand perception.

2.2. Business Profile Reviews

Google reviews play a significant role in the domain of electronic commerce as a crucial source of user-generated feedback that potential consumers strongly depend on to make educated purchasing decisions. Google reviews are used to establish trust and authenticity, encouraging business's efforts in search engine optimisation, building connections with the customers, and establishing a distinctive image towards competition, a strong online reputation, and brand loyalty. Google reviews can help businesses to improve their search

engine optimisation (SEO) rankings. Studies found that businesses that have a high number of positive Google reviews are more likely to appear higher in search engine results pages (SERPs) for relevant keywords [34–36].

Validation via social proof is achieved by using Google reviews, which effectively demonstrate real-life experiences of consumers who have engaged with the firm. Social proof is a psychological phenomenon that occurs when individuals look to the behaviour and actions of others to determine their own. In simpler terms, it is the idea that people tend to follow the actions of the crowd, assuming that if many others are undertaking an activity or task, then it must be the correct or desirable action to be performed. This influence may play a crucial role in influencing prospective buyers who are still in the process of making a choice [37].

The examination of user experiences via reviews provides vital insights into the perceptions and evaluations of consumers. These reviews provide a comprehensive understanding of the features that were well received and those that fell short of expectations, including many elements such as goods, services, and the whole purchase process. These insights have the potential to facilitate improvements in corporate operations. Google reviews can help businesses to improve their customer service.

A study found that businesses that respond promptly and thoughtfully to Google reviews are more likely to have satisfied customers [36]. The study investigates the influence of online reviews on business performance, specifically examining the impact of both numerical ratings and textual reviews on product sales. The research utilises a joint sentiment–topic model to identify topics and their corresponding sentiments in the review texts. Additionally, it suggests that numerical ratings act as a mediator for the effects of sentiments expressed in the textual reviews. The findings not only enhance the understanding of how electronic Word-of-Mouth (eWOM) affects product sales, but also shed light on the dynamic relationship between numerical ratings and textual feedback in influencing sales.

The use of Google reviews has the potential to enhance a business's efforts in search engine optimisation. The impact of these evaluations on local search results might enhance the prominence of the company when people search for relevant products or services. For example, research [38] highlights that when customer ratings are diverse and distinctive, they hold significant value for potential consumers in their decision-making process. Additionally, the study acknowledges the need for future research to validate findings across various specialised websites and to address challenges related to the reliability and validity of online social communication.

The process of responding to Google reviews, regardless of their content, provides companies with an opportunity to actively connect with their customers. Demonstrating attentiveness to issues and showing gratitude for favourable comments exemplifies exemplary customer service, fostering a sense of rapport.

The provision of unfavourable evaluations, although not the desired result, offers essential input for progress in several domains such as product development, service enhancement, and overall consumer satisfaction. Publicly addressing such complaints demonstrates a dedication to ensuring client satisfaction [39].

Favourable evaluations provide a distinct value proposition, setting one enterprise apart from its peers. When considering several options, a substantial number of good evaluations might potentially influence the decision in a favourable manner.

Reviews serve as a valuable collection of user-generated material that can be effectively used across many marketing platforms, including social media and the official website of the company. The material generated by users functions as a medium via which authentic consumer experiences are observed [40].

The process of long-term reputation building involves the accumulation of positive Google reviews, which plays a significant role in establishing a strong and positive online reputation. The reputation of a business serves as an attractive force for acquiring new consumers and fostering brand loyalty [41,42].

It is recommended to use a proactive approach in encouraging consumers to provide evaluations. One possible approach to achieve this objective is via the use of email reminders or the provision of incentives to encourage individuals to submit evaluations. It is important to immediately address all reviews. This demonstrates a strong commitment to client satisfaction and a dedication to delivering exceptional service.

It is important to maintain transparency about review policy. This communication aims to explain the approach used by our organisation in addressing counterfeit or deceptive evaluations.

2.3. Trust Trademarks Impact on Electronic Commerce

Trademarking, also referred to as trademark registration, is the legal procedure wherein a unique symbol, emblem, logo, name, phrase, or design linked to a specific product or service is formally recorded with the relevant government authority. This registration presents the owner with exclusive rights to employ the trademark in association with their offerings, affording legal safeguards against unauthorised usage. The primary objective of trademarking is to establish and safeguard the distinctive brand identity of a product or service in the market. It aids consumers in recognising and distinguishing the offerings of one company from those of others, playing a pivotal role in constructing brand awareness, reputation, and instilling trust among consumers.

The significance of trust in the realm of electronic commerce cannot be overstated, as it serves as the fundamental cornerstone upon which successful e-commerce enterprises are built. Buyers in the digital marketplace put great value on certainty and dependability, thereby elevating trust as a highly coveted asset.

Thus, the process of trademarking provides additional safeguards that enhance the perceived authenticity and credibility of a brand. The act of signalling a commitment to quality and consistency serves to build confidence among clients. Trademarks can help to build trust among consumers by signalling a commitment to quality and consistency. A study found that consumers are more likely to trust businesses that have a registered trademark [43].

The process of trademarking also plays a crucial role in the development of a distinct brand identity. The unique characteristics of a product or brand appeal to buyers and discourage the presence of counterfeit entities, hence strengthening the element of trust.

Legal safeguards are provided by a trademark, which provides a firm with the ability to seek legal remedies in cases of infringement. The adoption of a proactive posture serves to enhance trust among stakeholders by showcasing a steadfast dedication to upholding brand integrity. Trademarks can help to protect businesses from counterfeiters. A study found that businesses that register their trademarks are less likely to be victims of counterfeiting [44].

The very nature of a trademark has the potential to embody trust. It denotes a firm's commitment to upholding ethical standards and prioritising customer satisfaction, hence reinforcing the relationship between the client and the business. Within the digital domain, a proliferation of imitations is prevalent. A trademark serves as a protective measure against imitators, providing consumers with the assurance that they are engaging with the genuine organisation. Also, trademarks can help to create a positive brand image. A study found that consumers are more likely to have a positive impression of businesses that have registered trademarks [45].

The act of trademarking plays a significant role in fostering a favourable consumer impression. Buyers exhibit a higher propensity for engagement when a business allocates resources towards safeguarding its identity, thus demonstrating a dedication to their interests. Trademarks can help to increase customer engagement. A study found that businesses that register their trademarks are more likely to have engaged customers [46].

Trademarks possess significant value as assets for electronic commerce enterprises. The act of registering trademarks enables companies to safeguard themselves against counterfeiters, establish a favourable brand perception, enhance consumer involvement, and distinguish themselves from other entities.

There are many further advantages associated with the process of trademarking for e-commerce enterprises: enhanced brand recognition; the establishment of trademarks may contribute to the augmentation of client loyalty via the cultivation of trust and familiarity among customers; enhanced market penetration; and enhanced brand value. In the context of trademarks, sentiment analysis can be used to gauge public sentiment towards a brand or trademark. This could involve analysing social media mentions, customer reviews, or online discussions to understand how people perceive and talk about a particular trademark.

Combining both trademark analysis and sentiment analysis can provide valuable insights for businesses. For example, a company might use sentiment analysis to monitor how consumers feel about their brand and products, and then combine this with trademark analysis to ensure that their trademark is effectively representing the brand and not causing any confusion or negative sentiment. Ultimately, both types of analyses serve to protect and enhance a brand's reputation and market presence, with trademark analysis focusing on legal and commercial aspects, and sentiment analysis focusing on public perception and sentiment towards the brand.

2.4. Sentiment Analysis and Electronic Commerce

Within the domain of electronic commerce, sentiment analysis assumes a crucial function in assessing client feelings while maintaining the confidentiality of the origin. This technology explores the realm of consumer views while taking into consideration privacy considerations. Also, sentiment analysis can be used to gain valuable insights into customer sentiment, which can then be used to improve products, marketing, and customer service [47].

Sentiment analysis refers to the process of extracting customer sentiments from textual data. Through the analysis of product reviews, comments, and interactions on social media platforms, companies are able to obtain valuable insights into the emotional responses of customers, all while upholding their privacy [48–50].

The comprehension of consumer happiness encompasses a range of sentiments, spanning from positive joy to negative discontent, as revealed by sentiment analysis. This comprehension assists enterprises in refining their offers to correspond with client desires. The use of sentiment analysis plays a crucial role in the enhancement of product development as it enables the identification of aspects that elicit good responses from clients, as well as areas that need improvement. The use of a data-driven strategy facilitates the enhancement of items to achieve a greater level of resonance within the market [51].

E-commerce organisations use sentiment analysis techniques to customise marketing tactics. Businesses enhance their outreach endeavours by gaining an understanding of client responses to promotions and campaigns. The use of sentiment analysis offers a contemporaneous assessment of market sentiments. The ability to quickly respond to trends and concerns enhances the relevance of the brand [52].

The use of sentiment monitoring facilitates the identification of deficiencies in customer service. The use of prompt interventions has the potential to transform unfavourable attitudes into favourable experiences. Also, sentiment analysis can be used to identify areas in need of improvement in customer service, which can then be used to improve the customer experience [48].

Sentiment analysis examines the influence of product reviews on consumer purchase choices. Positive reviews have a significant impact on conversion rates since they contribute to the overall success of a product or service. Conversely, bad reviews provide valuable insights that may be used to identify areas for development. Also, sentiment analysis can be used to personalise the shopping experience for customers, which can lead to increased sales and customer satisfaction [48].

The recognition of emerging trends is facilitated by sentiment analysis, which enables firms to quickly adjust to changing client preferences.

The recognition of obstacles in sentiment analysis, such as the identification of sarcasm and the interpretation of context, is of utmost importance. It is essential for businesses to guarantee the attainment of correct analysis in order to facilitate successful decision-making. The ethical utilisation of resources is of utmost importance, since ethical concerns play a crucial role in decision-making processes. It is essential for businesses to exercise the use of sentiment analysis in order to maintain client confidence [52].

3. Materials and Methods

Customer reviews are used as a strategic approach to achieve desired outcomes in terms of enhancing traffic engagement and improving sales conversions [53]. The significance of favourable evaluations is derived from customer behaviour. The user provided a numerical reference [54]. Based on the findings of a survey conducted by Bright Local in 2023 [55], it was observed that customers allocate around 14 min of their time to examine reading activities prior to making a decision regarding a particular company. The research focused on the reasons behind users' selection of businesses, with a particular emphasis on the influence of a digital presence on the Google search engine, as well as the availability of favourable reviews. It was found that 56% of users were more likely to choose a company that fulfilled these criteria. The user's text does not contain any information or context to be rewritten in an academic manner. A company that has achieved a five-star rating has a 28% increase in click-through rates compared to a business without any rating.

Conversely, a business that has obtained a one-star rating results in an 11% decrease in click-through rates. Potential consumers are more likely to engage in a purchase when they are presented with favourable assessments that align with their individual requirements and anticipated outcomes [56–58]. The authors have garnered significant interest in the analysis of five-star and one-star reviews due to this particular rationale. In order to facilitate the investigation, it was vital to comprehend both the substance and the linguistic expressions used by the participants. The study methodology used for the purpose of interpreting the feelings of the participants is qualitative in nature. The structure is shown in Figure 1 and explained in detail below.

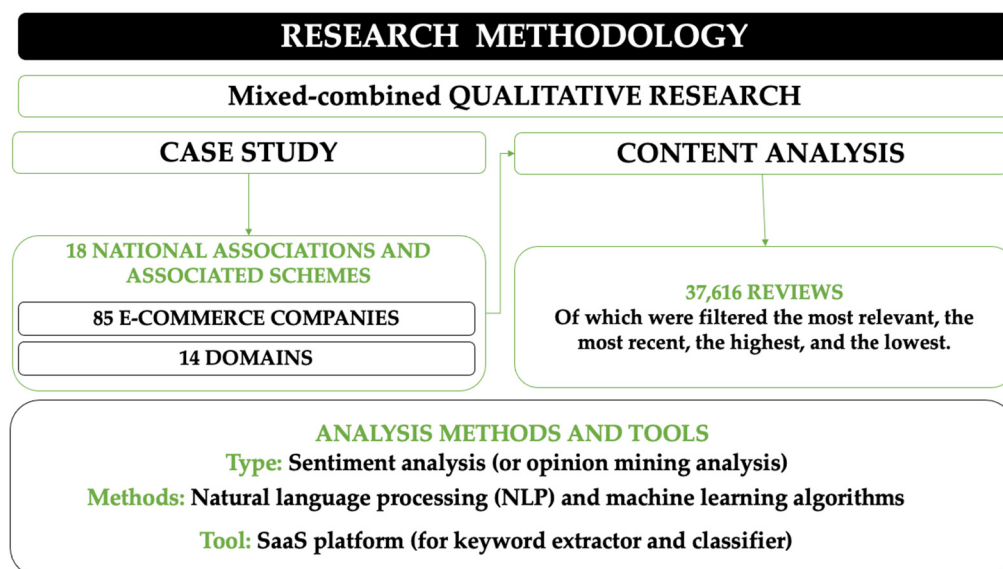


Figure 1. Research methodology. Source: Authors' conceptualisation.

By aiming to understand users' feelings behind search engine reviews, the authors appealed to a qualitative research method based on two complementary methods, namely case study and content analysis. Case studies are used by social scientists [59] to reveal individual behaviour, and to analyse a phenomenon as practice perspective [60]. The authors selected the method of analysing 18 case studies due to the practical nature of

the chosen topic. By including all the national associations and associated schemes at the regional, European level, the sample was qualified for relevant outcomes. Specifically, the authors used the case study of E-commerce Europe Trustmark [61]. The programme is designed to safeguard consumers, and the online shops involved are required to adhere to the E-commerce Europe Code of Conduct and uphold ethical standards in their operations. The authors consulted 18 national associations corresponding to each country enrolled in the programme (Appendix A). The process of collecting data concerning the chosen case studies began with a centralisation of all the participating European entities. Therefore, researchers accessed all the websites and identified the lists of beneficiaries of the programme. They were represented by national E-commerce companies that displayed the Trustmark label on their websites based on evaluated assets according to community standards. In order to confirm the status of each trusted entity, each company involved in the study was verified once again by checking that the label is that of a trusted online store on their website. Therefore, a database was created with the first five most performant companies listed for each country. In the final set, 90 online stores were extracted, corresponding to 14 domains (see Figure 2 for sample structure).

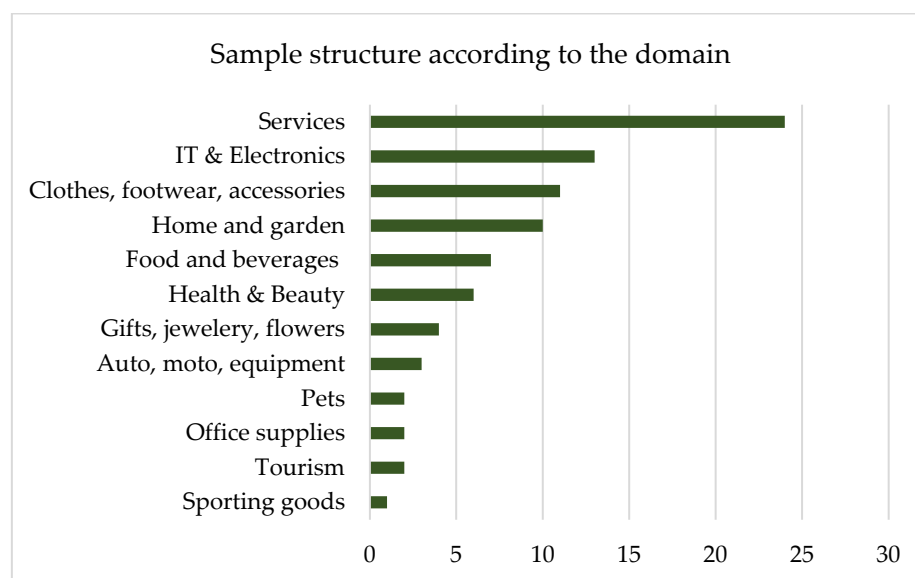


Figure 2. Sample structure according to the domain. Source: Authors' conceptualisation based on collected data.

After online stores collection, the authors analysed the digital presence of each online store on the Google search engine to identify their BP [62] public account. Out of 90 online stores, information was found for 85 of them. For all 85, the number of the reviews was identified and collected and the mean score was determined. During the process, the researchers interacted with 37,616 reviews in total for all 85 European online stores.

It is mandatory to mention that BP platform displays all the reviews publicly, with the opportunity of sorting them by four categories: (1) the most relevant, (2) the most recent, (3) the highest, and (4) the lowest. It is the standard of the platform, and the researchers found this aspect a useful one as a method to classify the reviews. Hence, they established the database by gathering the initial eligible reviews for examination. Ultimately, the average of the top five reviews for each sorting category was compiled, resulting in a total of 1680 reviews for analysis (see Table 1).

Table 1. The number of reviews according to sorting category for all 85 European online stores.

Sorting Category	Number of Reviews
The most relevant	425
The most recent	421
The highest (five stars)	421
The lowest (one star)	420
Total	1687

Source: Authors' conceptualisation based on data collection.

Henceforth, the content analysis was performed. Several studies show that the method of combining sentiment analysis (or opinion mining analysis) with content analysis generates impactful findings about recognising and interpreting human emotion [63], or helping businesses to understand customers' feelings [64]. The researchers analysed the selected case studies to demonstrate a method of using AI-based methods for business purposes. Companies are increasingly using NLP-equipped tools to extract insights from data and automate routine tasks (virtual assistants or chatbots are good examples) [65]. By demonstrating how feelings of users can be analysed using this technique, the researchers fulfil the aim of understanding the users' feelings behind the reviews. To show how simple it is for companies, specialists, or academics to use the method, the authors used a Software-as-a-Service (SaaS, which works through the cloud delivery model) platform, named MonkeyLearn [66]. It is mentioned in recent publications as a research method for similar purposes [67–70]. The platform provides pre-trained sentiment analysis models and is able to provide valuable insights about the sentiment (positive, negative, or neutral) and the confidence level. By classifying techniques through natural language processing and machine learning, keywords extractor and keywords cloud image were used to gather a visualisation on the topics described by users.

The authors selected MonkeyLearn AI-based tool due to its very effective way to extract information through the online platform. The academic references show that the application presents a 72.12% accuracy [71]. The platform presents five items provided for usage argumentation, namely: (1) the graphical user interface to create custom machine learning models to test; (2) pre-trained models available in public mode; (3) scalable cloud computing platform for usage; (4) API and SDKs (Python, Ruby, Node, Java, and PHP) that allows users to integrate the MonkeyLearn cloud computing engine with any software project, using any programming language; and (5) the necessary documentation needed for operation. Also, the application's model is organised into two families, one for classification and one for extraction [72].

The Indicator of relevance was collected to display the level of accuracy of the information extracted. The relevance score is a metric assigned for each word extracted with a cloud generator and it is calculated by multiplying the relative term frequency by another score (IFD) that measures the uniqueness of a word. By definition, IFD is the inverse frequency document and is a statistical metric that evaluates how relevant a word is to a document in a collection of documents [73]. It is part of the TF-IDF formula, which is presented below:

$$tf\ idf(t, d, D) = tf(t, d) \cdot idf(t, D) \quad (1)$$

where,

$$tf(t, d) = \log(1 + \text{freq}(t, d)) \quad (2)$$

$$idf(t, D) = \log\left(\frac{N}{\text{count}(d \in D : t \in d)}\right) \quad (3)$$

4. Results

In an attempt to fathom the reviewing patterns of users expressing negative sentiments, the authors made a noteworthy observation. They anticipated encountering extensive narratives and detailed accounts of their unfavourable experiences, particularly in the case of one-star reviews. However, contrary to their expectations, users did not articulate their emotions in text form. Additionally, the sentiment analysis algorithm identified a neutral tone of voice in both five-star and one-star reviews as the predominant emotional category (as indicated in Table 2). Another intriguing finding emerged as follows: even in the case of five-star reviews, the users' sentiments were not uniformly interpreted as positive. Surprisingly, a substantial proportion (81%) was classified as neutral.

Table 2. Descriptive statistics about users' feelings.

Sorting Category	The Most Relevant	The Most Recent	Five Stars	One Star
Mode	Positive feeling	Neutral feeling	Neutral feeling	Neutral feeling
Positive feeling frequency	241 (56.84%)	54 (12.8%)	79 (18.72%)	8 (1.90%)
Neutral feeling frequency	27 (6.37%)	341 (80.81%)	340 (80.57%)	343 (81.47%)
Negative feeling frequency	156 (36.79%)	27 (6.40%)	3 (0.71%)	70 (16.63%)

Source: Authors' conceptualisation based on descriptive statistics analysis.

The category of most pertinent reviews exhibited a more pronounced inclination towards positive sentiments compared to negative ones, underscoring an ideal scenario for any company. Interestingly, the influence of negative sentiments from other users appeared relatively subdued within the realm of these highly relevant reviews.

In order to unveil the prevalent themes associated with both high- and low-rated reviews, the authors constructed word clouds (see Figure 3). This visual representation offered a succinct yet insightful snapshot of the recurring topics and concerns expressed by reviewers across different rating categories.



Figure 3. The word cloud result for the (a) lowest and (b) highest category of reviews. Source: Authors' conceptualisation based on keywords extractor analysis.

The analysis reveals that aspects such as service, price, product, staff, and company hold notable importance across the board. Nevertheless, there are discernible distinctions in their respective emphases, as detailed in Tables 3 and 4. The relevance of each word was determined for every element using the methodology outlined in the study: by analysing the distribution of words to ensure a comprehensive evaluation of their significance within the context of the reviews.

Table 3. Distribution of words for reviews rated one star.

Topic	Service	Price	Product	Staff	Company
No. of times	105	91	61	58	48
Relevance	1	0.88	0.62	0.59	0.51

Source: Authors' conceptualisation based on sentiment analysis results.

Table 4. Distribution of words for reviews rated five stars.

Topic	Service	Price	Product	Company	Staff
No. of times	22	21	20	11	9
Relevance	1	0.96	0.91	0.53	0.45

Source: Authors' conceptualisation based on sentiment analysis results.

With regard to the discussion of the company, reviews awarded with a one-star rating exhibit a notably higher level of relevance. Interestingly, the aspects of service, price, and product maintain consistent prominence across both scenarios.

In order to gain deeper insights into the specific content addressed by users, Table 5 was meticulously created with the aid of a keyword extractor. The table serves as a valuable tool for categorising the key themes and concerns raised by reviewers.

Table 5. Keywords extractor results summary.

Five Stars Reviews		One-Star Reviews	
Aspect	Opinion	Aspect	Opinion
product	pleasant experience	store	written specie
experience	pleasant surprise	long time	not good service
yesterday	brought product	small animal	friendly people
second order tomorrow	pleasant experience	variety of products	negative comment
employee	friendly employee	product	sealed price
product	negative comment	presentable people	rude customer
price	slightly expensive price	emag brasov employee	really bad support
service	quite delicious food	shop	chic showroom
coffee shop	great coffee	product	very friendly employee
brand name	efficient service	product	great to have a place
dining experience	negative point	order	lousy service
star experience	extremely friendly staff	product	also available product
staff	stunning room	store	expired warranty
food	delicious food	order	not given information
faux fir tree	nice colour	product	wrong order
first time	fake tree	product	fast order processing
company	great company	product	negative comment
professional for professionals	best advice	sale	too many people
staff	top supplier	flower arrangement	mediocre flower arrangement
advice	reliable staff	product	broken leave
customer	wrong item	product	bad experience
service	wrong wiper blade	staff	pleasant staff
service	fast service	service	free ticket
different pasta	nice personnel	service	just fine board
pizza variation	charming restaurant	price	good price
shopping centre	good menu	order	sent order
price	cheap price	order	taken care
customer	wrong item	service	great service

Source: Authors' conceptualisation based on keywords extractor analysis results.

Furthermore, the study outcomes allowed us to highlight a potential performance expressed by the mean score of reviews (RMS) displayed on certified online stores' BP. By using artificial intelligence to run sentiment analysis, RMS can highlight the performance of

participating national association with its retailers as an indicator for trusted online stores. Consequently, the study offers a significant scientific contribution through the theoretical development of a proposed model for future investigation in this domain.

$$\begin{aligned} RMS_i = & \beta_0 + \beta_1 \sum_{i=1}^n R_i + \beta_2 \overline{ConfRelev}_i + \beta_3 \overline{maxSntRec}_i + \beta_4 \overline{SRec}_i + \beta_5 \overline{ConfRec}_i \\ & + \beta_6 \sum_{i=1}^n SntHigh_i + \beta_7 \overline{ConfHigh}_i + \beta_8 \overline{ConfLow}_i + \epsilon_i \end{aligned} \quad (4)$$

where the RMS_i is the mean score of reviews of retailers in i economy; R_i is the number of reviews in i economy; $ConfRelev_i$ is the confidence score of the most relevant reviews of retailers in i economy; $SntRec_i$ is the sentiment for the most recent reviews of retailers in i economy; $SRec_i$ is the average score of the most recent reviews of retailers in i economy; the $ConfRec_i$ is the confidence score of the most recent reviews of retailers in i economy; $SntHigh_i$ is the sentiment for the highest reviews of retailers in i economy; $ConfHigh_i$ is the confidence score of the highest reviews of retailers in i economy; and $ConfLow_i$ is the confidence score of the lowest reviews of retailers in i economy. The upper bar represents the mean score for the variables. Following the analysis, researchers identified that only two variables, namely $SRec_i$ and $ConfLow_i$ demonstrated significance as exogeneous factors (with a p -value $< \alpha$). The model's coefficient of determination is $R^2 = 0.80$, indicating a strong explanatory power, and the adjusted $\bar{R}^2 = 0.61$. Despite the limited findings obtained through regression analysis, it is important to note that the overall significance of the model has been verified by conducting Fisher's test (as evidenced by F-statistics = $0.02968 < 0.0$ (Appendix B).

5. Discussion

In the contemporary business landscape, the convergence of technological innovation and ethical considerations represent a paramount challenge. The study undertakes a pioneering endeavour, employing the sentiment analysis technique, under the aegis of AI. The approach addressed by the authors not only showcase the potential of AI-based methods in enhancing business, but also underscores the ethical consideration embedded in its implementation. Also, they exhibited insights to discern user sentiments and humancentric business strategies. The findings covered the responses for research questions and led to objective achievement (Figure 4).

Results according to the objectives

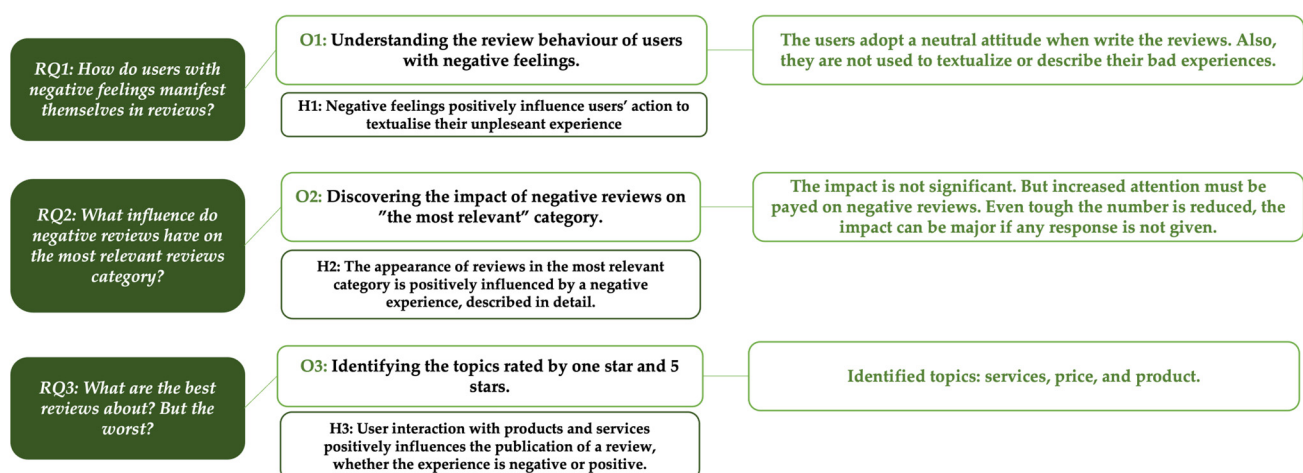


Figure 4. Research questions, objectives, hypotheses, and results of the study. Source: Authors' conceptualisation based on the content of the article.

Initially, in their endeavour to comprehend the reviewing patterns of users with negative sentiments, researchers uncovered a noteworthy revelation. They observed that users tend to not elaborate extensively on their unpleasant experiences. Instead, they often adopt a neutral tone of voice, refraining from expressing their sentiments as vehemently as a one-starred review might suggest. This fact shows that most users who rate their experience with a retailer with just one star typically aim to express their dissatisfaction with the worst feedback option, and not to describe or textualize their experience (which can be rated by up to 3–4 stars for unsatisfaction). Consequently, the initial hypothesis was refuted. Negative feelings do not positively influence user's action to textualize their unpleasant experience. By this outcome, the first objective (O1) was achieved.

The second objective (O2) assumed the impact of negative reviews as "the most relevant". It is not very high, but if the audience searches for negative reviews to find how the company reacted, it may possibly become risky for brands if a consequent community management activity responding to every review does not exist. On this topic, the second hypothesis was refuted as well.

Achieving the third objective (O3), the authors identified service, price, and product as pivotal themes that users tend to focus on when composing a review. This aligns with the acceptance of H₃.

Also, the authors tried to develop a model which can demonstrate the usage of artificial intelligence for business improvement purposes by discovering two variables which can contribute to the review mean score at the economy level.

The article presents a perspective on the usage of artificial intelligence for business purposes. By using sentiment analysis based on natural language processing and machine learning, the authors aimed for the findings of the research to demonstrate the potential that the development of science can have in harmony with market needs. By selecting the 85 case studies at the European level, the researchers wanted to convey the fact that in a growing field such as electronic commerce, technology can have a huge impact [21,32]. On the one hand, it can help analyse consumer behaviour and user actions in a difficult chapter to tackle without technology–content analysis for reviews [50,57]. The outcome of the research supports what the literature highlights in relation to reviews. The content can be used to interact, build trust, and communicate with users [40]. Based on the findings, knowing that users prefer to evaluate through a one-star review by not describing in detail their experience can represent an opportunity for marketers to use generated content from the audience to gain trust. From here comes the first advantage regarding the managerial implications.

The study findings seamlessly complement the earlier literature review in the first part of the paper. In the context of electronic commerce development, artificial intelligence emerges as a method for optimising the processes required to understand the consumer behaviour. Also, maintaining and demonstrating strong commitment to client satisfaction by building trust will represent key-factors in adapting to forthcoming trends.

In conclusion, the utilisation of artificial intelligence for business purposes, marketing strategies and content analysis have a profound influence in formulating humancentric approaches. This underscores the transformative potential that lies in leveraging advanced technologies for strategic business development and for the ethical deployment of AI, which is imperative for companies, experts, and academia.

6. Conclusions

The utilisation of sophisticated natural language processing (NLP) and machine learning methods by the authors has not only extended the boundaries of technical applications, but has also facilitated the more impactful utilisation of artificial intelligence (AI) by academics, managers, and experts. The authors enhance the existing approach in the literature by using a mix of case study, sentiment analysis, and content analysis. Their work showcases the efficacy of utilising a platform for analysis.

In business settings, the usage of artificial intelligence requires the adoption of tools and expertise so that managers and specialists can make their work more efficient and increase their availability for creating humancentric strategies worthy of Industry 5.0. It will represent both a competitive advantage in the market regardless of the field, but also a key resource in terms of surveillance for the future.

The academic environment will have to align itself with the radically changing requirements of the market and to embrace the artificial intelligence used in the training of future specialists who will be needed in the human-centred industry. Collaboration with the business environment must be a priority so that the education and training of students are aligned with market requirements. In both environments, the only certainty is change, and technology must be seen as an asset, not a threat. Used as such, it can streamline, adapt, and accelerate development in various fields. This is the reason why the authors of the paper focus on the use sentiment analysis in the transformation of reviews into business enhancements.

A key constraint of this research relates to the selected approach for examining the content of reviews. The range of accuracy in sentiment analysis exhibits a considerable variety, with results spanning from around 70% to above 90%. The extent of variability is contingent upon many aspects, including the intricacy of the text, the calibre of the dataset, and the level of sophistication shown by the applied model. However, it is important to acknowledge that previous research has shown models with lower levels of accuracy, highlighting the need for the development of sentiment analysis approaches that can be used effectively in actual, real-world situations. Additionally, the sentiment analysis reveals the limitations of linguistic variants. The intricacy of natural language poses challenges for software equipped with pre-trained algorithms and interpretation, potentially impacting its performance. The methodologies used in this context are unable to detect the presence of sarcasm, grammatical errors, or irony utilised by users within their assessments. The second category is characterised by the execution of qualitative research. Ensuring representativeness at the population level is not possible, owing to the inherent character and kind of the sample, which is itself non-representative. Nevertheless, due to the substantial amount of information that was analysed, the findings have the potential to serve as a basis for future study. Conversely, when conducting text or content analysis, this technique is seen as the most suitable.

Further research might represent broad research, by numerically expanding the sample, so that many online stores are covered, not only certified ones. Also, qualitative research at a national level must be performed, not only at the European level. From the point of view of the technology used, researchers can perform sentiment analysis not only by using keywords classifier and word clouds, but they also have the option to work with different tools to obtain detailed insights about topic labelling or intent detection.

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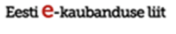
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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. E-commerce Europe Trustmark's participating national associations and their associated schemes.

No.	Country/Link	Association/Logo	No.	Country	Association/Logo
1.	Belgium www.becommerce.be		10.	Portugal www.confio.pt	 
2.	Czech Republic www.apek.cz		11.	Spain www.confianzaonline.es	 
3.	Denmark www.emaerket.dk		12.	Germany www.ehi-siegel.de	 
4.	France www.fevad.com		13.	Austria www.handelsverband.at	
5.	Greece www.greekecommerce.gr		14.	Switzerland www.handelsverband.swiss	 
6.	Ireland www.retailexcellence.ie		15.	Estonia www.e-kaubanduseliit.ee	 
7.	Italy www.consortionetcomm.it		16.	Sweden www.trygghandel.svenskhandel.se	 
8.	Netherlands www.thuiswinkel.org		17.	Latvia www.e-va.lv	
9.	Norway www.trygghandel.no		18.	Romania www.arro.org.ro	

Source: Authors' conceptualisation based on www.ecommercetrustmark.eu data.

Appendix B

Table A2. Regression statistics.

	Coefficients	Standard Error	t Stat	p-Value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	7.340034214	1.930176356	3.802779053	0.005215976	2.889039556	11.79102887	2.88903956	11.79102887
R	1.30973×10^{-5}	2.36342×10^{-5}	0.554166727	0.594612213	-4.14033×10^{-5}	6.75978×10^{-5}	-4.1403×10^{-5}	6.75978×10^{-5}
ConfRelev	-0.117664214	1.461281387	-0.080521257	0.937800623	-3.487385135	3.252056706	-3.48738513	3.252056706
SntRec	0.563153324	0.33226305	1.694902049	0.128540589	-0.203046643	1.32935329	-0.20304664	1.32935329
SRec	-1.930980471	0.742865266	-2.599368363	0.031648865	-3.644030847	-0.217930095	-3.64403085	-0.217930095
ConfRec	0.097931797	0.840684704	0.116490519	0.910135053	-1.840690607	2.036554201	-1.84069061	2.036554201
SntHigh	0.163408387	0.125235934	1.304804309	0.228239678	-0.125386196	0.452202969	-0.1253862	0.452202969
onfHigh	-0.427365704	1.703702935	-0.2508452	0.808256339	-4.356111718	3.501380311	-4.35611172	3.501380311
ConfLow	-3.149352107	1.013835726	-3.106373179	0.01452498	-5.487261483	-0.81144273	-5.48726148	-0.81144273

Appendix C

Table A3. Confidence level according to each category of reviews.

Reviews												
	The Most Relevant			The Most Recent			The Highest			The Lowest		
Label	Confidence	Average	Median	Confidence	Average	Median	Confidence	Average	Median	Confidence	Average	Median
All	41–100%	91%	98%	41–100%	80%	78%	70–78%	80%	78%	–50.00%	78%	78%
Positive	41–100%	91%	98%	41–100%	80%	78%	42–78%	80%	78%	55–100%	93%	97%
Negative	50–100%	92%	99%	52–100%	81%	78%	95–99%	96%	95%	50–100%	80%	78%
Neutral	43–87%	71%	74%	50–78%	77%	78%	50–78%	77%	78%	65–88%	78%	78%

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