

# A New Approach for Product Quality Check Based on Social Networks Opinions Analysis

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**Abstract**— In this paper, we aim to enhance the relevance of e-commerce web sites by a prior quality checking of proposed products. This checking is done by analyzing social networks and YouTube videos comments.

To achieve this objective, we have broken down the work into a few steps. The first one consists in scraping text from social networks groups and storing it in a NoSQL graph database. Each scraped word is linked to one or many reactions that are coming from the social network. Therefore, we can utilize the database as a knowledge source that associates each set of terms with a specific type of reaction: positive, negative or neutral. Afterwards, we use a TF-IDF based filtering method to keep only relevant words and eliminate those which are connected to all reactions. The advantage of this stage is the presence of a knowledge source that can be used for product quality checking.

In the e-commerce web site, data are coming from multiple e-commerce websites. The latter, offer products without quality checking. Concretely, we aim to allow users to check quality by a simple check button which call an implemented web service using human reactions and comments. After evaluating our approach, we have obtained an accuracy of 0,75. This result means that our method gives a three quarter of chance to have a good product.

**Keywords**- analysis, check, comment, e-commerce, quality, product, reaction.

## I. INTRODUCTION

E-commerce- websites fulfill a pivotal role by offering convenience and accessibility to consumers for online product browsing and purchasing. They serve as a platform for businesses to expand their reach globally, minimize market entry barriers, and promote competition and innovation. In the ever-expanding digital landscape, e-commerce- platforms have become indispensable tools, revolutionizing the way we engage in commercial activities.

One of the- main challenges in e-commerce is ensuring true quality. The- difficulty lies in assessing product quality without physical interaction. Customers heavily rely on product descriptions, images, and reviews, but these- may not always provide an accurate representation of the actual quality. As a result, customers may receive products that don't meet their expectations in terms of durability, functionality, or overall value. Moreover, inconsistencies in quality across different suppliers or sellers can further complicate the issue-. To address these challenges and ensure consistent delivery of high-quality

products, e-commerce platforms need to implement robust quality control measures and establish clear guidelines for product descriptions and images. Additionally, fostering transparent and reliable customer feedback mechanisms is crucial.

In this paper, we will explain the role of the human interaction to give implicit advice to improve researches for quality products. We will begin by a presentation of the related works, then we describe the main steps of our approach. Afterward, we will give an evaluation of our method. And finally, we will give a conclusion of this work.

## II. RELATED WORKS

Many studies have focused on improving recommendation systems and refining prediction accuracy. Researchers have also explored optimization aspects such as efficient data storage solutions. Additionally, there has been a significant emphasis on trust and personalization in the literature. Another important area of study is sentiment analysis. Other topics covered in the research include AI architecture, tools, methodologies, decision

making support, customer behavioral analysis, foundational concepts of AI, and intelligent agents. The distribution of different research areas can be seen in the figure below. [1].

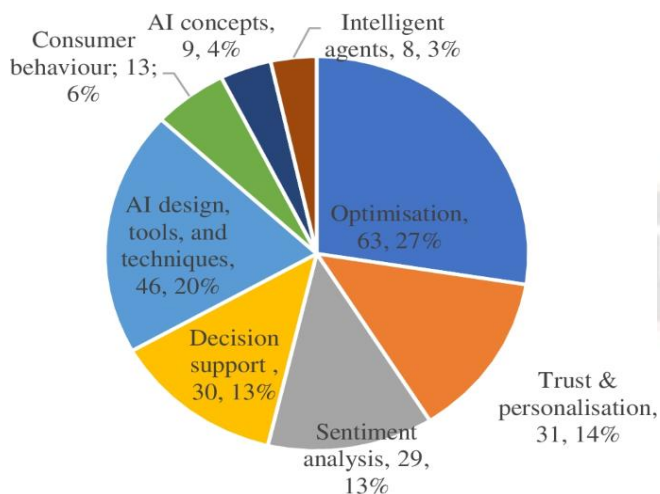


Figure 1. Classification of literature on AI in e-commerce

In the rest of this section, we will focus on some research areas like as quality, accessibility, satisfaction, human behaviors and trust.

#### A. Quality

Sai Kumar and al. examine in his paper [2] the website quality concerns from the perspective of e-commerce users. The concept of e-quality is crucial for establishing trust by offering value for money products and secure payment gateways. The study uses quality function deployment to identify key aspects of user-desired website quality. This approach enhances user satisfaction and encourages website reuse. The paper details the 12 core dimensions involved in evaluating website quality through its development and validation process.

Rehman and al. have extended understanding of customer behavior by introducing new variables to the UTAUT framework. He examines connections between e-shopping service quality, drivers like performance expectancy, and e-shopping intention, adoption, moderated by offline brand trust. Structural equation modeling and path analysis on 356 Pakistani e-shoppers reveal e-shopping service quality's influence on drivers, which impact intention and adoption. Offline brand trust moderates the link between drivers and intention [3].

In their research paper [4], Nasser and al. explore the factors influencing e-service quality in online shopping, defined as the gap between customer expectations during service encounters and before service delivery. Given the growing importance of e-service quality in e-commerce, monitoring and measurement have gained significance. Perceived risk, a well-studied concept in marketing, is relevant for understanding e-commerce payment system adoption. For Nasser and al., the internet's substantial impact on the Malaysian market has made online shopping and product information access more convenient.

#### B. Accessibility

In the paper [5], The authors studied e-commerce website accessibility, selecting the top 50 sites based on rankings. They used a modified methodology (WCAG-EM 1.0) and the Web Accessibility Evaluation Tool (WAVE) to assess accessibility. The findings showed a correlation between site ranking and accessibility barriers. Top accessible sites included Sainsbury's, Walmart, and Target. Main issues were contrast errors. The study suggests creating an AI-powered tool to automatically address accessibility issues for improved usability.

this study holds significance, especially during the COVID-19 era where e-commerce drives economic growth. The WAVE tool's applicability extends to enhancing website accessibility universally. The study recommends a dual approach: heuristic methods based on WCAG 2.1 for identifying barriers and automated assessments involving diverse users. Results show 55.8% of websites meet "AA" accessibility, with a low positive correlation (0.329) between site ratings and accessibility barriers. Issues include 25.6% lacking product images and 54.4% facing contrast problems. Collaboration among business, government, and academia is urged to establish inclusive web accessibility regulations.

#### C. Satisfaction

In their research paper [6], Bo Xiao and Izak Benbasat have introduced a typology of deceptive practices in e-commerce, offering insights into how online merchants deceive consumers on product websites. This typology can educate consumers and establish ethical benchmarks for online businesses. The study also develops a model explaining why consumers fall for deceptive practices and identifies factors influencing detection success. This model enhances our understanding of product-related deception in e-commerce and provides a foundation for further research. It also aids government and consumer organizations in devising effective solutions against online deception.

Khalid.A and al. [7] have evaluated e-commerce satisfaction in Saudi Arabia using a modified American Customer Satisfaction Index (ACSI) model. Analyzing 149 survey responses, the research finds that customer satisfaction hinges on factors like expectations, e-commerce service quality, and perceived value. Notably, perceived value is influenced by expectations and service quality, while service quality is influenced by expectations. This underscores e-commerce service quality as a crucial determinant of customer satisfaction, aligning with Saudi Arabian customers' focus on security and payment-related concerns.

In the realm of research, this study introduces a conceptual framework illuminating customer satisfaction within e-commerce systems, emphasizing customer expectations, service quality, and perceived value. Empirical evidence underscores their interconnectedness. Furthermore, these findings hold practical implications, guiding practitioners on effective strategies for enhancing customer satisfaction and optimizing e-commerce approaches.

#### D. Trust

Trust is simultaneously a complex, vague notion and an indispensable attribute integrated within e-commerce systems. Its connotations are multifaceted and profoundly context-dependent. Literature exploring trust integration in e-commerce mirrors this ambiguity, offering numerous articles but lacking a definitive theoretical framework for trust investigation. E-commerce fundamentally hinges on trust, making its establishment with customers vital for success. Consequently, there's a pressing requirement for explicit guidance on e-commerce attributes and operations nurturing consumer trust. In response, Beatty and al. [8] conducted a qualitative meta-study of empirical trust literature in e-commerce, addressing the field's immaturity. Major theoretical frameworks and a qualitative model were identified, integrating empirically recognized factors influencing consumer trust. While this model's complexity limits practicality, the authors examine its robust subsets, discussing their implications for website design. Ultimately, they outline pivotal conceptual and methodological areas warranting exploration in future research endeavors.

In the study conducted by Saw and al., the concept of trust is explored as both complex and essential within e-commerce systems [9]. The authors emphasize the absence of a definitive theoretical framework despite numerous articles on trust integration in e-commerce. The pivotal role of trust in e-commerce success is highlighted, with any e-commerce entity failing to establish trust doomed to failure. Urgent guidance on e-commerce attributes and strategies to foster consumer trust is underscored. Conducting a qualitative meta-study due to the evolving nature of the field, Saw and al. identify key theoretical frameworks and propose a qualitative model incorporating empirically recognized factors influencing consumer trust in e-commerce. They delve into subsets with strong literature support, discussing implications for website design, and outline crucial conceptual and methodological areas for future research.

The phenomenon of collusive spamming on e-commerce platforms significantly impacts consumers' purchase choices and disrupts equitable competition among sellers. In response, numerous strategies have been suggested to identify collusive spammers on these websites. However, these prevailing methods rely on manually crafted attributes, incurring high costs and time consumption. Given this constraint, Zhang and al. [10] propose an innovative approach for detecting collusive spammers, utilizing reinforcement learning and an adversarial autoencoder. Our approach involves modeling the dataset as a user-product bipartite graph, treating it as the agent's interactive environment, and employing a modified reinforcement learning algorithm to derive potential groups. Furthermore, the authors harness the Doc2Vec model to create embeddings for each candidate group and introduce an adversarial autoencoder-based one-class classification model for identifying collusive spammers. Empirical findings from real-world review datasets confirm that our proposed method outperforms existing approaches in terms of detection accuracy.

#### E. Behaviors

In the research paper [11], Sign and colleagues' research reveals the explosive growth of the e-commerce market, from

US\$ 13 trillion to an anticipated US\$ 55.6 trillion by 2027. They highlight the crucial role of Natural Language Processing (NLP) in evaluating product reviews and business models in this dynamic environment. Their study, using NLP and Machine Learning, analyzes an Amazon dataset to categorize sentences by sentiment, particularly labeling 'better' as positive and 'worse' as negative. NLP's significance in product classification amid the vast e-commerce landscape and its ability to predict sponsored and unpaid reviews is underscored, achieving a 79.83% validation accuracy using Fast Text and the Multi-channel Convolutional Neural Network.

In their research [12], Hernández and colleagues explore the factors influencing online purchasing decisions, with a focus on how e-purchasing experience moderates these influences. They distinguish between two groups: potential first-time e-customers and experienced e-customers. The study reveals that the motivations for first-time online purchases may differ from those driving repeat purchases. Importantly, customer behavior evolves as individuals gain experience from previous e-purchases, leading to shifting perceptions of e-commerce. While Internet experience consistently influences all users, the relationships between e-commerce perceptions and purchasing experience vary. These findings hold significant implications for e-commerce providers whose business models rely on understanding and adapting to e-customer behavior.

This study offers valuable insights for e-commerce providers whose business models and revenue generation are closely tied to the behavior of online customers. Nevertheless, it's essential to bear in mind that the outcomes might have been shaped by the influence of people culture [12](Spanish in this study).

Amid the global impact of COVID-19, including Saudi Arabia, consumer behaviors have shifted significantly towards increased online commerce. The study referenced in [13] aims to assess the factors influencing online shopping in the Saudi context during the pandemic. The analysis, focusing on product variety, payment methods, trust, convenience, and psychological factors, found that only three factors—product variety, payment method, and psychological factors—directly influenced online shopping during COVID-19. Convenience and trust, although important, did not significantly affect consumers' decisions due to the widespread adoption of online shopping during the pandemic. These findings can guide e-commerce businesses in adapting their marketing strategies to better meet consumer needs, particularly during crises.

In the fiercely competitive Chinese online market, companies like Alibaba and Tencent, global tech giants, are at the forefront. Alibaba has invested significantly in AI and established 3,200 offline e-stores with robotic systems. Tencent has also made strides in the online market, partnering with platforms like JD.com, VIP, and Pinduoduo. The research of Rashidin and al. [14] employs in-depth interviews and a model based on risk theory and customer resistance to change behavior (CRCB) to examine this phenomenon. AI-driven analysis, particularly decision tree-ANN, enhances transaction efficiency between buyers and sellers on these platforms and supports advanced credit risk assessment for sustainable e-commerce development.

However, this study has specific limitations. It solely focuses on Chinese e-commerce platforms (e.g., Alibaba and Tencent) and AI, which may be seen as a constraint. The absence of validation with non-Chinese platforms (e.g., Amazon, eBay) in global e-commerce markets is another limitation. Future research should consider experimental analysis to address possible sample bias and expand the study to include e-commerce users from different countries, facilitating empirical and comparative analysis of Chinese and other international e-commerce platforms, with a specific emphasis on leading platforms.

The study of Isaac and al. [15] investigates how artificial intelligence (AI) is reshaping the online shopping experience, particularly focusing on consumer interactions with AI components in e-commerce. It adopts the stimuli-organism-response (S-O-R) paradigm to analyze AI's impact on consumer engagement, going beyond purchase intentions. Various AI elements, including chatbot efficiency, image search, recommendation systems, and automated after-sales services, are examined. Findings reveal that these AI elements directly and indirectly influence observable consumer engagement behaviors. Additionally, the research highlights the moderating role of consumers' attention to social comparison, shaping the relationships between AI capabilities and consumer engagement. These insights offer valuable guidance for e-commerce platforms seeking to enhance the overall consumer experience.

In the paper of Deepanshand al. [16] underscores the symbiotic relationship between the development of electronic commerce and AI technology, examining the current state of AI application in e-commerce. It specifically delves into AI fields such as AI assistants, automated recommendation systems, and AI-driven optimal pricing strategies, shedding light on their impact on the e-commerce domain.

Anil KUMAR and al. [17] announce that the rapid evolution of computing technology has ushered in significant changes in various domains. Among these technological advancements, Artificial Intelligence (AI) has emerged as a potent force reshaping business practice and enhancing customer experiences. However, despite its transformative potential, AI applications are still in their early stages across industries, and the existing literature on the subject is fragmented. To address this gap, this study conducts a systematic review of 106 out of 170 analyzed literature sources, synthesizing research on AI's role in electronic commerce. The study sheds light on AI's current status, its applications in modernizing e-commerce, and its potential to reintroduce personalization and human touch into online shopping. This research aims to inspire further exploration of AI's applications in the e-commerce landscape.

In the Chatbots domain, Rob and al. [18] apply the Use and Gratification (U&G) theory to investigate consumer acceptance of Chatbots, a form of applied artificial intelligence (AI), within the context of online shopping in China. The study collected data through an anonymous online survey from 540 frequent online shoppers who are familiar with Chatbots. The findings from the data analysis reveal that utilitarian factors like "authenticity of conversation" and "convenience," along with hedonic factors such as "perceived enjoyment," contribute to users' favorable

attitudes towards Chatbots. However, concerns related to privacy and the relatively early stage of technology development have negatively impacted acceptance. In their paper they offer a valuable theoretical and practical insights into how Chinese consumers perceive Chatbots, serving as a valuable resource for e-commerce researchers, practitioners, and U&G theorists alike.

In the previous paragraphs, we gave an overview about the current research axis. Therefore, we finish the current section by the following conclusion:

The satisfaction of clients is related to the trust of the E-commerce application, the accessibility to the recommended products, the quality of products and all this can be discovered on analyzing behaviors and reactions of clients. In the next section, we are going to define a new process workflow to calculate relevance of products quality.

### III.CONTRIBUTION

In this work, we focus on the impact of human reactions to decide which product is more recommended. To achieve this objective, we need a real time database that can provide us the ability to identify which word is associated with a specific human reaction. For this purpose, we used essentially Facebook reactions and commentaries. To achieve this, we started by scraping Facebook and YouTube posts. Then, we save the relationship between words and reactions in a Neo4J graph database. Finally, we use this graph to identify the implicit opinion about a specific product.

Our main objective is to develop a new efficient measurement of global satisfaction regarding an implicit sentiment analysis. To accomplish that, we used the TFIDF method to calculate weight and index of each word in the database. The attributed weight is used to give the strength degree between each couple word/reaction. To be accepted, a word must be associated with a maximum of two different reactions.

After including the words, a cleaning step is required to remove stop words and reduce the noise within the database. To have a relevant disambiguation of words, and considering the different words morphology, we have combined Neo4J and ElasticSearch to take advantage of the automatic word morphological variations. As result, we generated a graph of relevant words with weighted relationships.

In terms of implementation in the E-commerce Website, a check button is attached to each product to search into the database the number of positive and negative words are related to the product in question.

The following figure illustrate the main steps of our quality check approach.

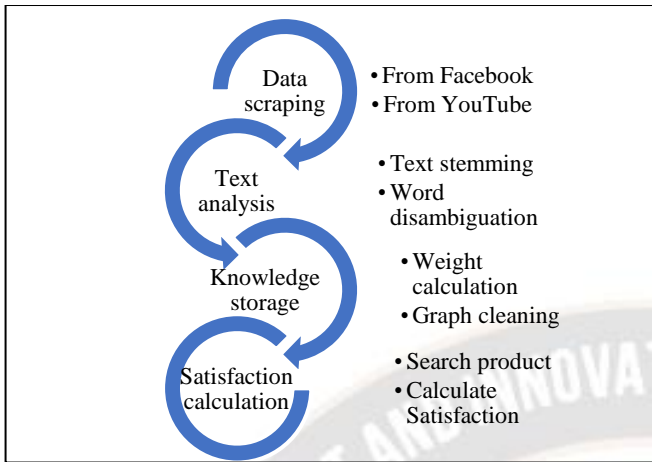


Figure 2. Steps of quality check

The detailed steps will be explained in the next sections.

A. *Process workflow*

Our approach is based on a process workflow that is organized in three steps: data ingestion, quality evaluation and e-commerce WebApp.

The process workflow that summarizes the mentioned steps is described by the following BPMN diagram in Figure 3:

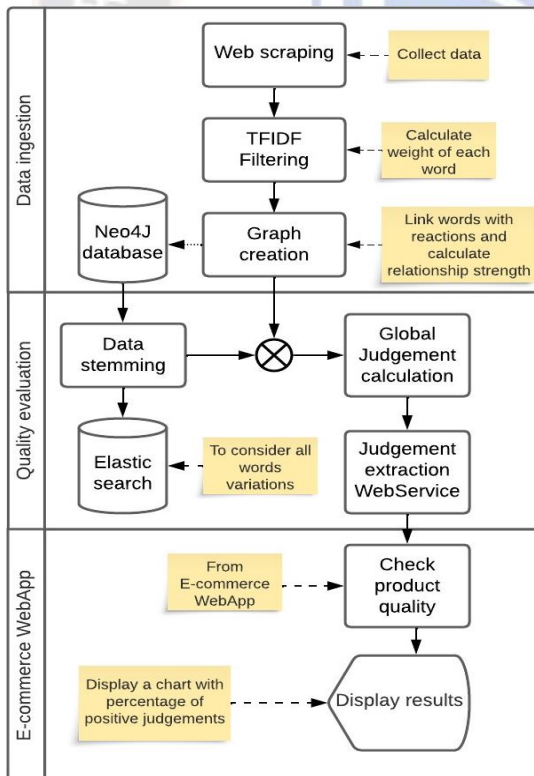


Figure 3. Process workflow of quality check

A. *First layer: data ingestion*

The first step in this workflow is to scrap data from Facebook and YouTube. The result of web scraping is then presented as a Json file (Figure 4):

```
[
  {"Tom Vencill": "Cecile Paroton"},
  {"Daisy Yar": "Louis Vuitton is great."},
  {"Soumia Soussou": "J'adore"},
  {"Léa Chloé": "amazing"},
  {"Belkys Perez": "DONT BUY ANUTHING FROM THEM. GO TO"},
  {"Laila Laila": "واعرين بزااف"},
  {"Silvia la Mariachi": "Good"},
  {"Stephen Smith": "Looks good"},
  {"Eehc Amar": "Is it loud enough for a party throug"},
  {"Steven Halliday": "Awesome"},
  {"Kathleen Wilson": "Cool"},
  {"Abdelaziz el hichou": "سي"},
  {"Renzjohn Echallas": "I want it"}
]
```

Figure 4. Example of Json scraped comments

The figure 4 illustrates the scraped comments along with the corresponding user account names. In addition, the reactions and comments related to posts are initially saved in unrefined state inside Neo4J database. The figure 5 illustrates the information that is saved.

post_text	comment	like	love	care	haha	wow	sad	angry
Make a promise with House Ambassador Chloe Gra...	Cecile Paroton	85.0	28.0	1.0	NaN	NaN	NaN	NaN
Make a promise with House Ambassador Chloe Gra...	Cecile Paroton	85.0	28.0	1.0	NaN	NaN	NaN	NaN
J-hope and the Keepall. The House Ambassador s...	Louis Vuitton is great.	1915.0	1704.0	39.0	1.0	15.0	NaN	NaN
J-hope and the Keepall. The House Ambassador s...	J-hope is the perfect model every fashion comp...	1915.0	1704.0	39.0	1.0	15.0	NaN	NaN
J-hope and the Keepall. The House Ambassador s...	J-hope is the perfect ambassador for Louis Vuit...	1915.0	1704.0	39.0	1.0	15.0	NaN	NaN
Pacific Chill: an invigorating Cologne. In an ...	Top faninEla Caire	845.0	171.0	2.0	1.0	1.0	1.0	1.0
Pacific Chill: an invigorating Cologne. In an ...	When a man meets love, he will become tolerant...	845.0	171.0	2.0	1.0	1.0	1.0	1.0
Pacific Chill: an invigorating Cologne. In an ...	~	845.0	171.0	2.0	1.0	1.0	1.0	1.0
Pacific Chill: an invigorating Cologne. In an ...	Trương Văn Phan	845.0	171.0	2.0	1.0	1.0	1.0	1.0
Pacific Chill: an invigorating Cologne. In an ...	Top faninNejmi Taskin	845.0	171.0	2.0	1.0	1.0	1.0	1.0

Figure 5. Example of scraped data reactions

In the Neo4J database, the scraped raw data are presented as a graph, where nodes represent words and reactions, and edges represent weighted relationships.

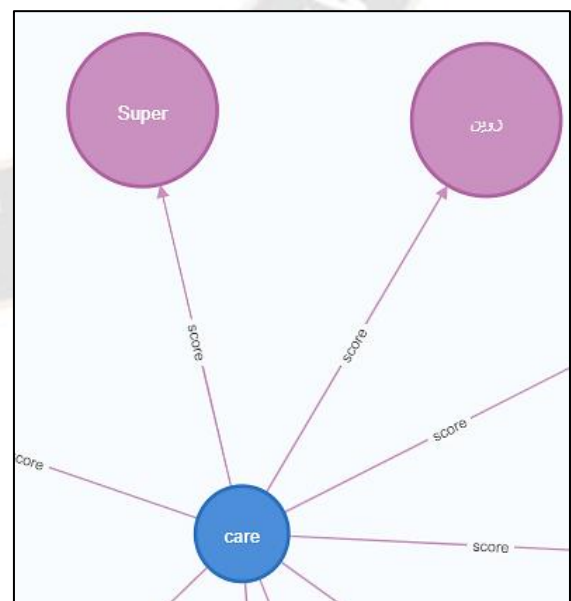


Figure 6. Example of Neo4J reaction/word graph

As illustrated in Figure 6, in the raw graph, multiple words are linked with all reactions. Therefore, these words cannot be used to define a specific reaction. Thus, a cleaning step is necessary to remove all words linked with all reactions. To accomplish this, we used a filtering layer. Then, we apply a TFIDF method to remove stop words to keep just terms that can be used index element. This method can be also used to calculate the weight of each word to know the relationship strength between word and reaction. The result is presented as a graph that can helps to know the reaction state near to a specific word. To have a complete judgement calculation, we have to perform a morphological variation by a word stemming and analysis. The comments can be written in different languages and dialects. Even local languages are taken into account and can be used in the index.

**B. Second layer: quality evaluation**

As shown in Figure 6, words can be represented in various formats. When a user searches for a word, it may exist in the database but in a different format. To fix this problem, it's important to use a stemming program, which is done automatically using Elasticsearch as a second database storage. Then, we have developed a web service to get reaction type associated to a specific word. We have to know that products names are also in the database and will be searched by users to check product quality.

When a user publishes a post about a product, we get some comments that can be positive, negative or indifferent (type of reaction). To know what comment is positive, negative or indifferent, we first query Elasticsearch database to get the type of reaction associated with the keywords in the comment. Figure 7 shows an example of judgement retrieval.

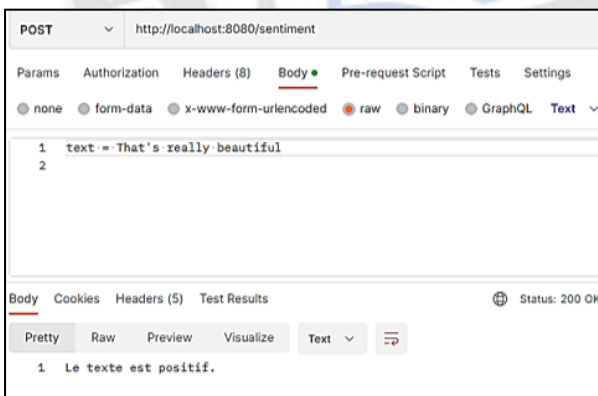


Figure 7. Check judgement webservice

Finally, we count positive and negative comments related to a given product and we calculate percentage of each type: positive, negative and indifferent. To extract judgement, we have developed a web service using Java and Spring Boot framework.

**C. Third layer: e-commerce web app**

In the third layer, we developed the E-commerce Web App, it shows products that come from two sources: manual source and scraped source. The manual source is what the user posts in

the E-commerce WebApp. The scraped source is what the WebApp extract from some other E-commerce websites. The question about the legality of scraping products leads as to say we redirect user to the original web site from which the product originates. Therefore, our objective is just checking quality by human interactions and comments. Figure 8 provide a screenshot of check product interface.



Figure 8. Shortcut of check quality interface

In this interface, user can just click on the check button to receive a summary chart which gives an idea in percent about the product quality. In the evaluation section bellow, we will take in consideration just positive and negative comments.

**IV. EVALUATION OF RESULTS**

To evaluate our method, we have used a sample of 100 products and 100 users. Then, we asked these users to assess product quality using a dedicated form that contain three buttons: Positive, negative and indifferent. An overview of the experimental results is presented in Table 1:

TABLE 1: OVERVIEW OF THE COLLECTED DATA

N°	TP	TN	FP	FN
1	60	23	8	9
2	57	21	3	19
3	54	10	12	24
4	45	30	5	20
5	23	53	11	13
6	64	16	8	12
7	22	50	9	19

**True Positives (TP):** TP represents the number of truly positive observations that were correctly identified as positive.

**True Negatives (TN):** TN represents the number of truly negative observations that were correctly identified as negative.

**False Positives (FP):** FP represents the number of truly negative observations that were incorrectly identified as positive.

**False Negatives (FN):** FN represents the number of truly positive observations that were incorrectly identified as negative.

In our context, we have several products to classify by multiple users. To achieve this, we calculated the sum of the confusion matrix elements. Table 2 presents our obtained confusion matrix.

TABLE 2: CONFUSION MATRIX

		Reality	
		Positive	Negative
Observed	Positive	TP=1465	FP=284
	Negative	FN=444	TN=807

According to the confusion matrix above, we have calculated the evaluation metrics in the following table:

TABLE 3: EVALUATION RESULT

<b>Accuracy</b>	0,75733333
<b>Precision</b>	0,80182462
<b>Recall</b>	0,74689082
<b>F1-score</b>	0,7721787

An F1-score = 0.772178703 indicates striking a balance between precision and recall, which means that the process is making accurate positive predictions while effectively capturing the majority of actual positive cases.

By this result, we remark that the using of user comments and reactions had a positive effect on the product quality check. The main advantages are the use of a real time database and the consideration of any language.

## V.CONCLUSION

Overall, this work aims to meet the needs of users by providing them with a user-friendly platform to assess the quality of products before purchasing them. To have an idea about the quality of products, we have used the user comments and reactions. Here, the user experience is a primordial factor to decide which product is more recommended.

The use of a graph database is an important phase in the global process. It helps to define a set of relationships which can't be used only in our work, but it allows other works to have benefit.

As a future works, we will attempt work on the effect of the geographic localization to recommend the good quality products. And finally, we aim to use that to check quality depending to the countries or cities.

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