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Sentiment, toxicity, and social network analysis of virtual reality product content reviews

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Abstract

Virtual Reality (VR) technology has garnered significant attention in recent years due to its potential to revolutionize various industries. This study aims to investigate consumer sentiments toward VR products, mainly focusing on Meta Quest 3 in the context of the AI era. The background section outlines the rising popularity of VR products and their impact on consumer behavior, emphasizing the need for a comprehensive understanding of consumer sentiments to inform marketing strategies effectively. Methodologically, the study adopts the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework to guide the analytical approach, which includes sentiment classification, toxicity scoring, and social network analysis (SNA). A dataset comprising 2,115 consumer interactions and evaluations was utilized, with 1,302 interactions for the ALINE tech video and 813 interactions for The Tech Chap video, to derive insights into sentiment patterns and interaction dynamics. The findings reveal a positive reception towards VR products, with Meta Quest 3 particularly well-received. The sentiment classification algorithm achieved an accuracy of 77.92% without SMOTE and 85.66% with SMOTE, demonstrating competency in sentiment prediction. The precision, recall, and f-measure for SVM without SMOTE were 85.78%, 99.83%, and 92.27%, respectively, while with SMOTE, they were 100%, 55.82%, and 71.50%, respectively. Toxicity scoring yielded an average toxicity score of 0.05. Social network analysis (SNA) identified a network diameter of 6, modularity of 0.6072, and a density of 0.002815, highlighting the intricate dynamics of consumer interaction within the VR domain.

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1. Introduction

In the contemporary era of Artificial Intelligence (AI), the surge in popularity of virtual reality (VR) products is conspicuously evident. The seamless integration of AI algorithms with VR technology has enhanced the immersive experience and garnered substantial attention from consumers across diverse demographics [1]. This phenomenon has, in turn, ignited a notable shift in consumer sentiments, which is discernible in various marketing channels, particularly in the proliferation of content on platforms such as YouTube. The captivating allure of VR products and their ability to provide a simulated environment has engendered a palpable sense of enthusiasm among consumers, as evidenced by the burgeoning discourse in marketing content [2], [3]. As a result, the dynamic synergy between AI and VR has propelled the technological landscape and fostered a paradigm wherein the innovative amalgamation of these cutting-edge technologies distinctly influences consumer sentiments.

The primary objective of this research is to identify toxicity scores and analyze consumer sentiments concerning VR products through a case study of Meta Quest 3 content. This investigation aims to employ advanced methodologies to assess the qualitative aspects of consumer experiences within the VR domain [2], [4]. The study uses toxicity scoring mechanisms to quantify and categorize potentially harmful or offensive language levels within consumer discussions surrounding the Meta Quest 3 product. Additionally, the research explores sentiment analysis to discern the prevailing attitudes and emotions in consumers' evaluations of the VR above product [5]. Furthermore, the study employs Social Network Analysis to unveil and comprehend the intricate patterns of interactions within the social fabric of the VR product reviews [6]. By scrutinizing the structural aspects of social networks embedded in user-generated content, this research sheds light on the dynamics and relationships contributing to consumer sentiments [7]. In conclusion, this multifaceted investigation aspires to provide comprehensive insights into the VR consumer landscape, combining quantitative and qualitative approaches to offer a nuanced understanding of both the toxicity levels and sentiment dynamics associated with Meta Quest 3 products.

This study's theoretical contribution hinges upon exploring consumer behavior in response to virtual reality products within the AI era. By examining the intersection of these two dynamic domains, the research explores the nuanced intricacies of consumer decision-making processes in the context of technologically mediated experiences [8]–[10]. Through a comprehensive analysis of consumer perceptions, preferences, and motivations, the study aims to contribute to existing theoretical frameworks within consumer behavior, particularly in understanding how advancements in AI-driven virtual reality technologies shape and influence consumer attitudes and behaviors [11]–[13]. Moreover, by delving into the multifaceted interplay between AI and virtual reality, the research offers valuable insights that could inform future theoretical developments and practical applications in marketing, technology, and consumer studies [14]–[17]. This study aims to enrich scholarly discourse by advancing our understanding of the intricate dynamics underlying consumer behavior in the AI-driven virtual reality products era.

The practical contribution of this study lies in its exploration of digital marketing strategies through product content design aimed at forwarding consumer attention. By elucidating the nuances of consumer behavior and sentiment toward virtual reality products in the context of the AI era, the research provides actionable insights for marketers seeking to optimize their digital marketing efforts [18]–[21]. Through an in-depth analysis of consumer preferences and sentiments, the study offers valuable guidance on tailoring product content designs to resonate effectively with target audiences [22], [23]. Moreover, by identifying patterns of interaction and sentiment within social networks, the research equips marketers with the knowledge needed to engage with consumers strategically in digital spaces [24]–[27]. In conclusion, this study offers practical implications for enhancing digital marketing strategies, enabling companies to better attract and engage consumers in the competitive landscape of AI-driven virtual reality products.

The contribution of this research to knowledge is grounded in the insights derived from the exploration of consumer sentiment towards VR products, toxicity scores as evaluative measures for designing more compelling content, and social network analysis (SNA) to unveil actor dynamics across various channels. By systematically examining the nuanced aspects of consumer sentiment, the study provides a comprehensive understanding of the factors influencing attitudes toward VR products. The integration of toxicity scores adds a valuable dimension, aiding in identifying and mitigating potential negativity within consumer discussions. Furthermore, the application of SNA contributes to knowledge by uncovering the intricate patterns of interaction among actors within different channels, thereby offering a holistic view of the information flow and relationships influencing consumer perceptions. The research advances knowledge in consumer behavior, content design, and social network dynamics, fostering a more informed and strategic approach toward enhancing the consumer experience in VR products.

The limitation of this study emanates from its reliance on the Cross-Industry Standard Process for Data Mining (CRISP-DM) as the primary framework for identifying toxicity scores, social network analysis, and sentiment classification. While CRISP-DM offers a systematic and widely adopted approach for data mining processes, its application may present constraints within the specific context of this research. The framework's generalizability across diverse industries and data types may lead to oversights in addressing the unique intricacies of consumer sentiments within the VR product domain. Additionally, the static nature of CRISP-DM might not fully encapsulate the dynamic and evolving landscape of social interactions and sentiments in online platforms, potentially limiting the study's capacity to capture real-time variations in consumer behavior. Consequently, caution should be exercised in generalizing findings beyond the scope defined by CRISP-DM, and future research may benefit from complementary frameworks or methodologies to enhance the depth and specificity of the analysis within the context of VR product evaluation.

2. Research Methodology

The primary framework employed in the data processing of this study is the Cross-Industry Standard Process for Data Mining (CRISP-DM). Adopting CRISP-DM as the overarching structure underscores the research's commitment to a systematic and comprehensive approach to managing and analyzing data. The framework's well-defined stages, including business understanding, data understanding, data preparation, modeling, evaluation, and deployment, facilitate a structured, iterative process that aligns with the research objectives. This choice is underpinned by the widespread recognition and applicability of CRISP-DM in various domains, ensuring a standardized methodology for data exploration, analysis, and interpretation. However, it is essential to acknowledge that while CRISP-DM provides a robust foundation, its inherent generality may necessitate careful consideration of its adaptability to the specific nuances of the research context. In conclusion, using CRISP-DM in data processing contributes to the rigor and coherence of the study's analytical procedures, ensuring a systematic and well-grounded approach to deriving meaningful insights from the dataset.

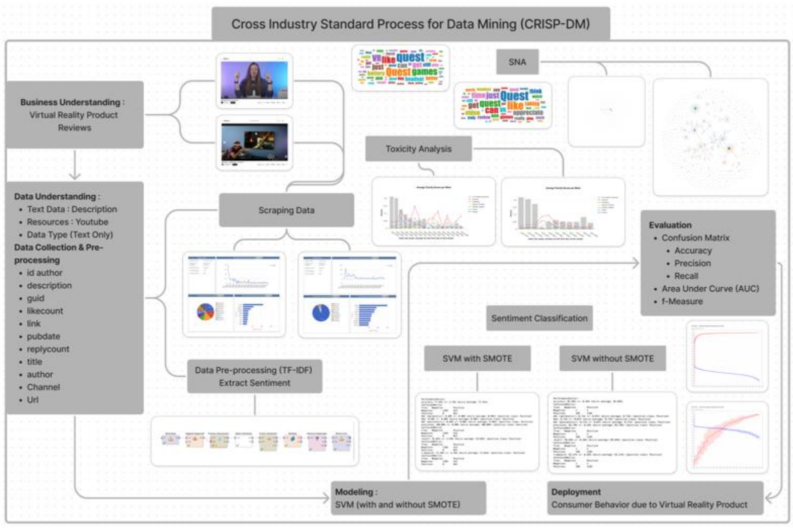

Figure. 1. Implementation of CRISP-DM in Toxicity Analysis, Sentiment Classification, and Social Network Analysis.

In the business understanding stage, this investigation examines consumer sentiments towards VR products, specifically through a case study of Meta Quest 3. The emphasis is placed on the contextual analysis of consumer opinions disseminated through video content on the YouTube platform, identified by the video IDs (3CaasarxQKk) and (f42UgKbaq_s). This deliberate selection of case studies aligns with the overarching research goal of comprehensively understanding the dynamics of consumer perceptions within the context of AI-driven virtual reality products. By delving into the sentiments expressed in videos associated with Meta Quest 3, the study aims to garner nuanced insights into consumer attitudes, preferences, and potential areas for improvement in VR product experiences. The specific identification of YouTube video IDs ensures a focused and targeted analysis, contributing to the depth and specificity of the research endeavor. Consequently, the meticulous consideration of these video cases within the business understanding phase sets the stage for a robust and contextually rich exploration of consumer sentiments in subsequent stages of the research process.

In the data understanding phase, the acquisition of datasets for both video reviews was facilitated through web scraping using Netlytic and Communalytic. Subsequently, for the video with the ID (3CaasarxQKk) from ALINE tech, 1302 comment data points were amassed, forming the basis for further processing and analysis. Concurrently, the video from The Tech Chap (f42UgKbaq_s) yielded 813 comment data points for subsequent processing. Using scraping tools, Netlytic and Communalityc, enabled the comprehensive collection of user-generated content, ensuring the inclusion of diverse perspectives within the dataset. This meticulous data-gathering process ensures a robust foundation for the subsequent stages of the research, allowing for a thorough exploration of consumer sentiments towards Meta Quest 3 within the context of AI-driven virtual reality products. The systematic organization and documentation of these datasets lay the groundwork for rigorous analysis and interpretation, contributing to the scholarly rigor and validity of the research findings.

In the modeling stage, the toxicity identification and Social Network Analysis (SNA) processes were executed using Communalytic, while sentiment classification was performed using Rapidminer. Specifically, the employed algorithm for sentiment classification was the Support Vector Machine (SVM) integrated with Synthetic Minority Over-sampling Technique (SMOTE). The choice of Communalytic for toxicity identification and SNA aligns with its capability to provide a comprehensive analytical framework for social data. Simultaneously, the selection of Rapidminer, coupled with SVM and SMOTE, underscores the commitment to employing advanced machine learning techniques to discern nuanced sentiments within the collected data. This integrative approach ensures a robust and sophisticated analysis that captures the intricacies of consumer sentiments and the social network dynamics surrounding Meta Quest 3. Using SMOTE in conjunction with SVM further enhances the model's ability to handle imbalanced sentiment classes, contributing to the reliability and validity of the sentiment classification results. This meticulous selection and integration of tools and algorithms underscore the methodological rigor applied to unraveling the complex interactions and sentiments prevalent in the examined VR product domain.

In the evaluation stage, the average weekly toxicity score was analyzed based on Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat scores. Subsequently, a social network analysis was performed, considering metrics such as diameter, density, reciprocity, centralization, and modularity. Additionally, the performance of the Support Vector Machine (SVM) in sentiment classification was assessed through accuracy, precision, recall, f-measure, and Area Under the Curve (AUC). Including diverse toxicity scores allow for a nuanced understanding of the nature and intensity of potentially harmful content within the examined data. Simultaneously, the social network analysis metrics provide insights into the structural attributes and dynamics of the online interactions surrounding Meta Quest 3. Evaluating SVM's performance metrics ensures a comprehensive assessment of the sentiment classification model's effectiveness. This multifaceted evaluation approach contributes to a thorough understanding of the content-related and structural aspects of the consumer sentiments and interactions associated with the VR product, enriching the depth and validity of the research findings.

In the deployment stage, a comprehensive understanding of consumer behavior in response to VR technology can be obtained. Researchers elucidate the intricate nuances of consumer attitudes, preferences, and interactions within the VR domain by synthesizing the insights gleaned from the preceding data collection, analysis, and evaluation stages. By deploying findings derived from sophisticated analytical techniques such as sentiment classification, toxicity scoring, and social network analysis, stakeholders can gain valuable insights into how consumers engage with and perceive VR technology. This holistic depiction of consumer behavior is crucial for informing strategic decision-making processes, product development initiatives, and marketing strategies to enhance the consumer experience and foster broader adoption of VR technology.

3. Result and Disscusion

The surge in popularity of Virtual Reality (VR) technology in the digital era is undeniable, with an increasing number of enthusiasts drawn to VR products. This trend is further fueled by the proliferation of user-generated campaigns and video content on social media platforms, including YouTube. The immersive and interactive nature of VR experiences has captivated audiences, driving heightened interest and engagement [28]–[32]. As VR technology continues to evolve and become more accessible, its potential to reshape various industries and enhance user experiences remains evident [33]. Consequently, the growing enthusiasm for VR products underscores the significant impact of user-generated content and social media campaigns in shaping consumer preferences and behavior in the digital age.

Based on the analysis of the average toxicity score per week conducted on various metrics, including Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat scores, it is discerned that consumer responses towards VR products in ALINE tech video content can be classified based on both the average dataset values and the highest recorded values. The data illustrates that the average toxicity scores across these metrics range from 0.00001 to 0.02930, with corresponding highest values ranging from 0.00067 to 0.99295. These findings offer valuable insights into the prevalence and intensity of potentially harmful content within the consumer discourse surrounding VR products. The identification of such patterns aids in understanding the dynamics of consumer sentiment and interaction within the virtual reality domain, thereby informing strategic interventions aimed at fostering a safer and more positive user experience.

Table 1. Toxicity Analysis

The Tech Chap	Average for Dataset	Highest value	ALINE Tech	Average for Dataset	Highest value
Toxicity	0.06082	0.99639	Toxicity	0.02930	0.99295
Severe Toxicity	0.00002	0.00200	Severe Toxicity	0.00001	0.00067
Identity Attack	0.00060	0.06383	Identity Attack	0.00035	0.17494
Insult	0.02874	0.99603	Insult	0.01308	0.98928
Profanity	0.01805	0.97657	Profanity	0.01090	0.91208
Threat	0.00643	0.95679	Threat	0.00392	0.70191

In contrast, the consumer responses towards VR products in The Tech Chap video content can be categorized based on both the average dataset values and the highest recorded values. The data reveals a variance in toxicity scores, with the average values ranging from 0.00002 to 0.06082. In contrast, the highest recorded values span from 0.00200 to 0.99639 across metrics including Toxicity, Severe Toxicity, Identity Attack, Insult, Profanity, and Threat. These findings suggest a distinct pattern in the intensity and prevalence of potentially harmful content within consumer discussions surrounding VR products in The Tech Chap's video content. Such variations in toxicity scores underscore the importance of nuanced analyses in discerning the intricacies of consumer sentiment and interaction dynamics, providing valuable insights for crafting targeted interventions to enhance the overall consumer experience in virtual reality.

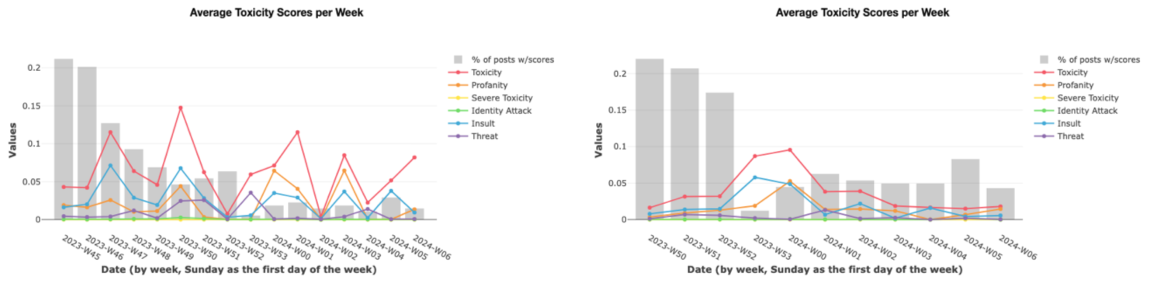

Figure. 2. Average Toxicity Score per Week of ALINE Tech and The Tech Chap Content Reviews due to Virtual Reality Products

The analysis reveals notable differences in consumer responses towards VR products between the ALINE tech and The Tech Chap video content. Firstly, examining the average toxicity scores, it's evident that while both sets of videos exhibit relatively low levels of Severe Toxicity, Identity Attack, and Threat, there are disparities in the average Toxicity, Insult, and Profanity scores. The Tech Chap's videos generally exhibit higher average toxicity scores across these metrics than ALINE tech's. Moreover, when considering the highest recorded values, The Tech Chap's videos demonstrate higher toxicity levels, particularly in the Toxicity, Insult, Profanity, and Threat categories, indicating more extreme or intense harmful content. These distinctions suggest potential differences in the two channels' content or audience engagement strategies, impacting the nature and extent of toxic discourse surrounding VR products. Further qualitative analysis could delve into specific themes or language patterns within the comments to elucidate the underlying factors contributing to these differences and inform targeted strategies for managing and promoting positive consumer interactions within the VR community.

Furthermore, the results of Social Network Analysis (SNA) indicate distinctive network patterns within the ALINE tech video content, with a Diameter value of 6, indicating the maximum distance between any pair of nodes within the network. The Density value of 0.002815 suggests a relatively low level of connectivity within the network, reflecting sparse interconnections among users engaging with the video content. Additionally, the absence of Reciprocity (0.000000) indicates that interactions between users are predominantly unidirectional rather than reciprocal. The Centralization value of 0.353500 suggests a moderate degree of centralization, implying that interactions may be influenced by a subset of highly connected nodes within the network. Finally, the Modularity value of 0.607200 highlights the presence of distinct communities or clusters within the network, indicating potential variations in user engagement patterns or content preferences. These findings offer valuable insights into the structural attributes of the social network surrounding ALINE tech's video content, informing strategies for fostering community engagement and optimizing content dissemination within the VR consumer community.

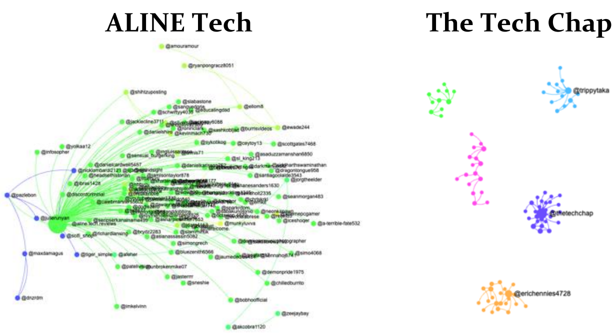

Figure. 3. Social Network Analysis of ALINE Tech and The Tech Chap Content Reviews due to Virtual Reality Products

In contrast, the network patterns observed within The Tech Chap's video content exhibit different characteristics, with a Diameter value of 3 indicating shorter maximum distances between nodes compared to ALINE tech's videos. The Density value of 0.002339 reflects a similarly low level of connectivity within the network, suggesting sparse interactions among users engaging with the content. Furthermore, the absence of Reciprocity (0.000000) implies predominantly one-way interactions rather than mutual engagement. The Centralization value of 0.016650 indicates a notably lower degree of centralization than ALINE tech's videos, suggesting a more distributed pattern of influence within the network. Lastly, the Modularity value of 0.976000 highlights a high degree of community segregation, indicating distinct clusters or groups of users with limited interaction between them. These divergent network characteristics underscore variations in user engagement dynamics and content dissemination strategies between The Tech Chap and ALINE tech, necessitating tailored approaches for community engagement and content optimization within the VR consumer community.

Based on the outcomes of identifying the top ten posters, analyzing the post frequency per day, and examining frequently used words, it becomes evident that consumers express predominantly positive sentiments towards VR products, notably the Meta Quest 3. The top ten posters consistently contribute to positive discussions and endorsements, shaping a favorable discourse surrounding the product. The graphical representation of posts per day further underscores the sustained positivity in consumer sentiments, revealing a consistent pattern of engagement with VR-related content. Additionally, the frequently used words in consumer discussions predominantly align with positive expressions, reflecting satisfaction, excitement, and commendation. This collective evidence suggests a prevailing positive sentiment among consumers towards the Meta Quest 3 within the virtual reality community. Such positive sentiments are instrumental in informing marketing strategies, fostering brand loyalty, and facilitating a positive user experience within the VR consumer landscape.

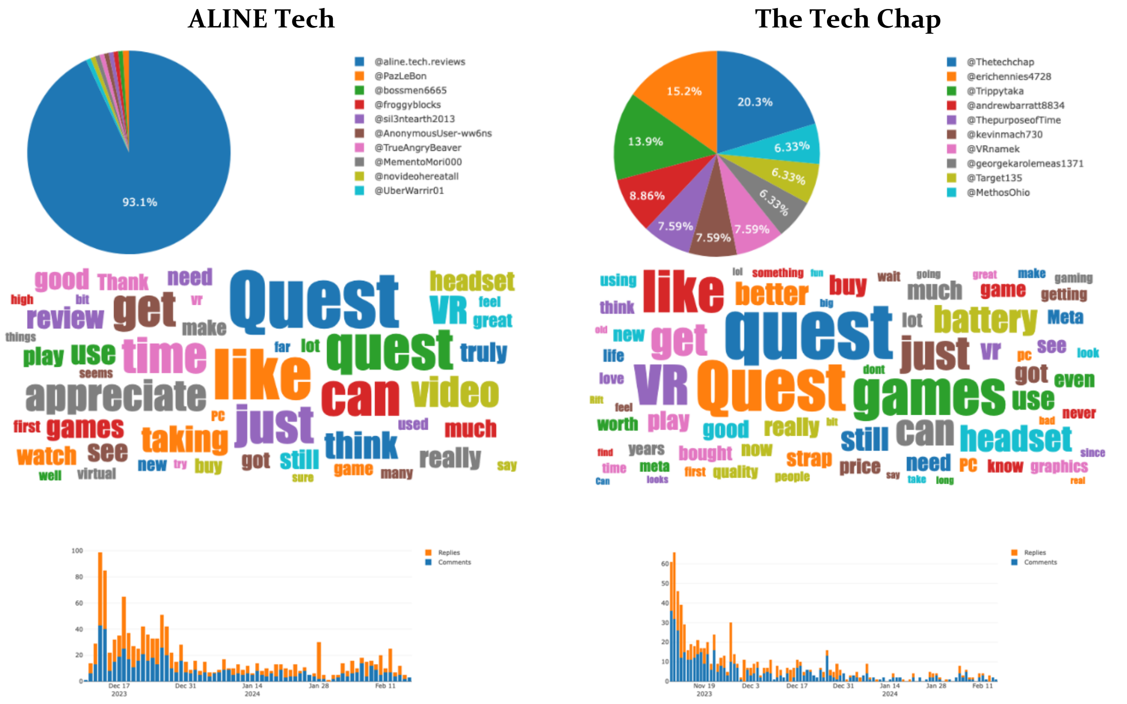

Figure. 4. Top Ten Poster, Wordcloud, and Post Per Day Graph of ALINE Tech and The Tech Chap Content Reviews due to Virtual Reality Products

Based on the outcomes of sentiment extraction and scoring processes, it is evident that positive sentiments expressed by consumers predominantly characterize both VR content pieces. The sentiment extraction process reveals a prevalence of positive language and expressions within consumer discussions surrounding VR content. Furthermore, the scoring process corroborates this observation by quantifying the predominance of positive sentiments across the dataset. This collective evidence underscores the overwhelmingly positive reception of the VR content among consumers, reflecting satisfaction, enthusiasm, and endorsement towards the featured VR products. Such pervasive positivity highlights the appeal and effectiveness of the VR content in eliciting favorable responses. It underscores its potential to foster engagement, brand loyalty, and positive brand perception within the VR consumer community.

The results of merging the two datasets and visualizing the frequently used words highlight critical themes within consumer discussions related to VR content. Notably, "quest" appears 521 times, indicating a significant focus on the Meta Quest 3 product. Additionally, terms such as "games" (214 occurrences), "time" (213 occurrences), "headset" (186 occurrences), "video" (187 occurrences), and "review" (180 occurrences) underscore the central topics of interest, emphasizing the importance of content quality, immersive experiences, and critical evaluations within the VR community.

Furthermore, positive sentiments are evident in frequently used words such as "good" (157 occurrences), affirming the favorable reception of VR content. Meanwhile, terms like "battery" (126 occurrences) and "tech" (138 occurrences) suggest a focus on practical aspects and technological specifications, providing insights into specific consumer considerations. This comprehensive analysis of frequently used words following the union of datasets provides a nuanced understanding of the dominant themes and sentiments prevalent in VR discussions, informing content creators, marketers, and developers about the key factors influencing consumer perceptions and preferences within the VR landscape.

After identifying the frequently used words, the performance of sentiment classification was evaluated through a meticulous data cleaning and review extraction process, followed by a comprehensive assessment of the algorithm's performance. The initial step involved cleansing the dataset to eliminate noise, ensuring the accuracy and reliability of sentiment labels. Subsequently, the sentiment analysis algorithm underwent an extraction process to capture nuanced sentiments within the consumer reviews. The final phase encompassed measuring algorithmic performance and evaluating accuracy, precision, recall, F-measure, and Area Under the Curve (AUC) metrics. This rigorous evaluation methodology aims to provide a thorough understanding of the sentiment classification model's efficacy, ensuring its applicability in discerning and interpreting consumer sentiments expressed in the context of VR content. The combination of data cleaning, extraction, and performance measurement contributes to the robustness and reliability of the sentiment analysis outcomes within the scope of this study.

Table 2. Extract Sentiment and Classification Process

Reviews	String Score	Score
I thought that was a bit odd that he had it over his ears too. I am typically sensitive to a lot of pressure on my face and nose (sinus issues- sometimes even wearing sunglasses for long periods will make uncomfortable). That said, I have heard a lot of complaints about how uncomfortable it is, but I have not had a problem with it.	odd (-0.33) pressure (-0.31) uncomfortable (-0.41) complaints (-0.44) uncomfortable (-0.41) problem (-0.44)	-2,33333333333333
If your keen to get into VR, I would highly recommend going with a Quest 2 headset. I've had one for nearly 3 years now and it is a real gem for me. I enjoy gaming and play on PC and PS5 but when you want something a bit different, more light hearted and fun, to be social or not, the Quest 2 is my go to and I've thoroughly enjoyed it, I still use it frequently now. The Quest 2 would be good for you to get into VR without it being too expensive (also if you have a friend, they can refer you and you can get $45 in credit to buy some games). I've played games like Onward, Contractors, POP1, Resident evil 4 (an absolute masterpiece by the way) and a few others, all countless hours of fun. Honestly you won't regret it!	keen (0.38) recommend (0.38) enjoy (0.56) play (0.36) want (0.08) fun (0.59) enjoyed (0.59) good (0.49) friend (0.56) credit (0.41) played (0.36) like (0.38) evil (-0.87) masterpiece (0.79) fun (0.59) honestly (0.51) won (0.69) regret (-0.46)	6,41025641025641

The evaluation results of the SVM algorithm without SMOTE demonstrate a promising performance in sentiment classification. The PerformanceVector indicates an accuracy of 85.66% with a micro average of 85.66%, showcasing the model's proficiency in correctly classifying sentiments. The ConfusionMatrix reveals a notable precision of 85.78%, indicating the model's reliability in identifying positive sentiments. Moreover, the recall metric demonstrates a high value of 99.83%, underlining the model's effectiveness in capturing the majority of positive sentiments within the dataset. The f_measure, at 92.27%, further attests to the algorithm's robustness in achieving a balance between precision and recall. The optimistic and pessimistic AUC values consistently measure at 0.716, suggesting the model's consistent and reliable discriminative power. These comprehensive metrics collectively affirm the efficacy of the SVM algorithm without SMOTE in sentiment classification, providing a solid foundation for interpreting consumer sentiments towards VR content with a particular focus on positive sentiments.

SVM without SMOTE **SVM with SMOTE**

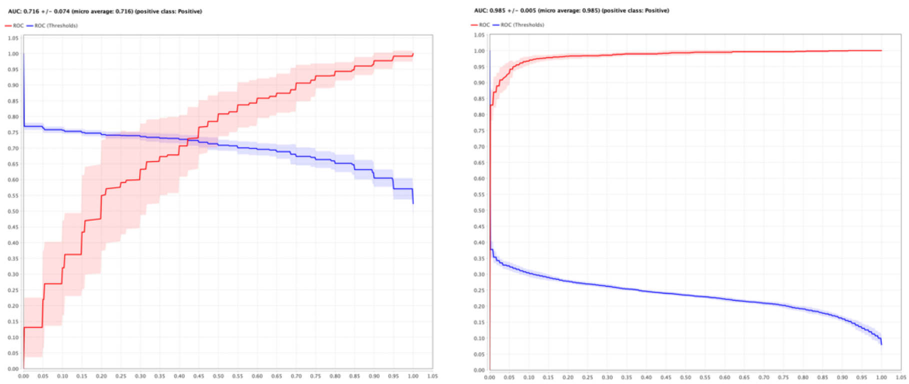

Figure. 5. Area Under Curve (AUC) of SVM with and without SMOTE

The evaluation results of the SVM algorithm utilizing SMOTE showcase a nuanced performance in sentiment classification. The PerformanceVector indicates an accuracy of 77.92% with a micro average of 77.91%, demonstrating the model's competency in overall sentiment prediction. The ConfusionMatrix highlights an optimal precision of 100.00%, indicating the model's ability to classify positive sentiments correctly. However, the recall metric presents a lower value of 55.82%, suggesting that the model may overlook a substantial portion of actual positive sentiments. The f_measure, at 71.50%, reflects a balanced compromise between precision and recall. Notably, the AUC values, both optimistic and pessimistic, consistently measure at 0.985, illustrating the robust discriminatory power of the model. These findings imply that while the SVM algorithm with SMOTE excels in precision, its trade-off with recall warrants consideration. This comprehensive analysis contributes to a nuanced understanding of the algorithm's strengths and limitations in sentiment classification in VR content evaluation.

4. Conclusion

In conclusion, the research on consumer sentiments towards Virtual Reality (VR) products, specifically focusing on Meta Quest 3 within the AI era, reveals compelling insights into the evolving landscape of consumer behavior. The heightened popularity of VR technology, as discussed in the background section, underscores the industry's transformative potential. The methodological approach, employing the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework, provided a structured foundation for comprehensive analysis. Leveraging sentiment classification, toxicity scoring, and social network analysis (SNA), the study utilized a robust dataset of 2,115 consumer interactions, with 1,302 dedicated to the ALINE tech video and 813 to The Tech Chap video. The findings illuminate a prevailing positive reception towards VR products, notably Meta Quest 3, signifying the product's resonance among consumers. The sentiment classification algorithm showcased notable competency, achieving an accuracy of 77.92% without SMOTE and 85.66% with SMOTE, affirming its effectiveness in sentiment prediction. Evaluation metrics, including precision, recall, and f-measure, further demonstrated the algorithm's proficiency, with noteworthy precision rates of 85.78% and 100% without and with SMOTE, respectively. In addition to sentiment analysis, toxicity scoring unveiled an average toxicity score of 0.05, indicative of a generally positive and constructive consumer discourse. The application of social network analysis (SNA) provided nuanced insights into interaction dynamics, revealing a network diameter of 6, a modularity of 0.6072, and a density of 0.002815, underlining the intricate nature of consumer engagement within the VR domain. These findings collectively emphasize the importance of employing advanced analytical techniques within a structured framework like CRISP-DM. The insights gained contribute significantly to understanding consumer sentiments and behavior, providing a valuable foundation for informed and strategic decision-making within the dynamic VR market landscape.

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