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Social Network Analysis and Sentiment Classification of Extended Reality Product Content

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Abstract−This study explores Extended Reality (XR) products, specifically focusing on the Apple Vision Pro, to elucidate consumer perceptions and the underlying social dynamics of these innovative technologies. This research delves into Extended Reality (XR) products, specifically focusing on the Apple Vision Pro, aiming to understand consumer perceptions and social dynamics surrounding these innovative technologies. By leveraging sentiment analysis and Social Network Analysis (SNA) alongside CRISP-DM and SVM algorithms, this study provides a comprehensive insight into sentiment patterns, network structures, and influential factors within the XR community. A multi-faceted approach is adopted to achieve the research objectives. Sentiment analysis and SNA dissect sentiment patterns and uncover network structures within the XR community. The CRISP-DM framework guides the research process, ensuring systematic data analysis and interpretation. SVM algorithms classify sentiments, providing a robust analytical framework for understanding consumer sentiments towards XR products. The analysis yields significant insights into XR consumer perceptions and social dynamics. The calculated network metrics, including a density of 0.000124, absence of reciprocity, centralization value of 0.001331, and modularity value of 0.999000, shed light on crucial network dynamics within the XR community. Examining frequently used words reveals prevalent topics within the XR discourse, providing valuable context for understanding consumer sentiments. Furthermore, the evaluation of SVM algorithms demonstrates commendable performance metrics, with the SVM without SMOTE achieving an accuracy rate of 84.33%, precision of 84.67%, recall of 99.28%, and f_measure of 91.39%. In comparison, the SVM with SMOTE exhibits an accuracy of 81.82% and a precision of 97.58%. This research contributes valuable insights into the consumer landscape of XR products, mainly focusing on the Apple Vision Pro. By combining sentiment analysis, SNA, and established methodologies, the study offers a nuanced understanding of consumer perceptions and social dynamics within the XR community. These findings inform strategic decisions and contribute to advancements in XR technologies, offering valuable insights into the efficacy of sentiment analysis techniques in understanding consumer sentiments.

Keywords: Extended Reality; SNA; Sentiment; Classification; Product

1. INTRODUCTION

In the digital era, particularly in the aftermath of the Covid-19 pandemic, extended reality (XR) products have gained remarkable popularity. The primary reason for this surge lies in the inherent capacity of XR technologies to bridge physical distances and facilitate immersive experiences, thus addressing the heightened need for remote interaction and engagement during social distancing [1]. Furthermore, the versatility of XR applications across various domains, including education, entertainment, healthcare, and business, has underscored its significance as a transformative tool in navigating the challenges posed by the pandemic and beyond [2]. As such, the widespread adoption of XR solutions reflects a growing recognition of their potential to reshape conventional modes of communication, collaboration, and experience consumption in the contemporary digital landscape [3]–[5]. In conclusion, the ascent of XR products after COVID-19 underscores their instrumental role in addressing societal needs and fostering innovative approaches to human interaction and engagement in the digital age.

Extended reality (XR) is a compelling and popular digital medium for enhancing work performance. The immersive nature of XR technologies provides users with interactive and simulated environments conducive to heightened productivity and engagement [6]. Research indicates that integrating XR tools in professional settings leads to improved training outcomes, enhanced task efficiency, and more excellent retention of information [7]–[9]. Moreover, the versatility of XR applications across industries such as manufacturing, healthcare, and education underscores its potential to revolutionize traditional work methodologies [10]–[12]. Consequently, the burgeoning adoption of XR in professional contexts reflects a growing acknowledgment of its capacity to optimize work processes and foster innovation [13]. In conclusion, the widespread embrace of extended reality signifies its transformative impact on augmenting work performance and heralds a promising trajectory for its continued utilization in diverse occupational domains.

Extended reality (XR) represents a digital innovation with transformative potential. This innovative technology amalgamates elements of virtual reality (VR), augmented reality (AR), and mixed reality (MR) to create immersive and interactive experiences beyond the confines of physical reality [14]. XR's ability to blend the digital and physical worlds seamlessly offers novel communication, education, entertainment, and business avenues [15]. Scholars and industry experts view XR as a groundbreaking advancement poised to redefine human-computer interaction and revolutionize various sectors [16], [17]. As such, the emergence of extended reality underscores the ongoing evolution of digital technologies and heralds a paradigm shift in how individuals perceive and engage with their surroundings [18], [19]. In summary, the advent of extended reality epitomizes the dynamism of digital innovation and signals a transformative trajectory for future technological advancements.

The dissemination of extended reality (XR) products packaged within video content and distributed through platforms like YouTube elicits diverse public sentiments. This medium makes XR experiences accessible to a broad audience, transcending geographical and temporal boundaries [20]. However, the reception of such content varies, with some viewers expressing awe and fascination at the immersive nature of XR technology [21]. In contrast, others voice concerns regarding potential privacy implications, ethical considerations, or the blurring of virtual and real-world boundaries [22]. Despite these varying perspectives, integrating XR within video content on platforms like YouTube signifies a significant shift in digital storytelling and audience engagement strategies [23]. In conclusion, the multifaceted reactions to XR content on YouTube underscore the complex interplay between technology, society, and media consumption habits, highlighting the need for critical discourse and ethical reflection in adopting emerging digital innovations.

The importance of this research lies in its contribution to advancing our understanding of consumer perceptions and behaviors towards extended reality (XR) products, particularly in the context of the Apple Vision Pro. By employing sentiment analysis and social network analysis (SNA) methodologies, this study offers valuable insights into the intricate dynamics shaping consumer sentiments and interactions within the XR community. Furthermore, the utilization of advanced techniques such as CRISP-DM and SVM algorithms enhances the robustness and accuracy of sentiment classification models, providing a solid foundation for strategic decision-making in XR development and marketing initiatives. Ultimately, this research not only fills existing gaps in academic literature but also offers practical implications for industry stakeholders, enabling them to better leverage consumer sentiment to drive innovation and adoption in the XR landscape.

The foundation of this research builds upon previous studies investigating consumer perceptions and behaviors towards extended reality (XR) technologies. Existing literature has explored various aspects of XR adoption, including user experiences, technological advancements, and market trends. However, a notable research gap exists concerning the nuanced analysis of consumer sentiment and social dynamics surrounding specific XR products, such as the Apple Vision Pro. While previous research provides valuable insights into broader XR adoption trends, there is a scarcity of studies focusing on the intricacies of consumer sentiment towards individual XR products and their implications for technology development and marketing strategies. Therefore, this research aims to address this gap by conducting a comprehensive analysis of consumer sentiments and social networks within the XR community, with a specific focus on the Apple Vision Pro, thereby contributing to a deeper understanding of consumer perceptions and behaviors in the XR landscape.

The urgency of this research underscores the importance of identifying public sentiments regarding extended reality products and analyzing social networks through review data from content published on the YouTube platform. Understanding public perceptions is critical in shaping the development, adoption, and regulation of extended reality technologies [24]. By examining user-generated content and feedback, researchers gain insights into the factors influencing public opinion, such as user experience, privacy concerns, ethical considerations, and societal impact [25]. Furthermore, leveraging data from YouTube reviews allows for a comprehensive analysis of the broader social discourse surrounding XR products, facilitating informed decision-making by policymakers, industry stakeholders, and technology developers [26]. In conclusion, this research initiative is vital to fostering a nuanced understanding of public sentiment towards extended reality, thus informing future advancements and ensuring responsible deployment within society.

This research's practical and theoretical implications are significant in advancing our understanding and application of extended reality (XR) technologies. By examining public sentiments and social network dynamics surrounding XR products on platforms like YouTube, this research offers valuable insights for policymakers, industry practitioners, and researchers. The findings can inform the development of more user-centered XR products, addressing concerns and preferences identified through user feedback. Theoretically, the research contributes to the growing body of knowledge on digital innovation adoption and societal responses to emerging technologies. Moreover, it sheds light on the intricate interplay between technology, society, and media platforms, enriching scholarly discourse in these domains. In conclusion, this research provides actionable recommendations for industry stakeholders and expands our theoretical understanding of the implications of extended reality within contemporary digital ecosystems.

The contribution to knowledge of this research is notable, particularly in its exploration of public sentiment towards extended reality (XR) products and the analysis of social networks through YouTube data. The study enhances methodological rigor by employing the Cross Industry Standard Process for Data Mining (CRISP-DM). It facilitates a systematic approach to data analysis, thereby strengthening the validity and reliability of the findings. However, it is essential to acknowledge the limitations of this research, primarily concerning its methodology and instruments. While CRISP-DM offers a structured framework for data mining, its application in analyzing public sentiment on social media platforms may encounter challenges related to data quality, bias, and interpretation. Thus, future research endeavors could explore alternative methodologies or refine existing approaches to address these limitations and deepen our understanding of public perceptions towards XR products.

2. RESEARCH METHODOLOGY

2.1 Gap Analysis of Extended Reality Topics using Vosviewer

The research gap in extended reality (XR) topics presents a compelling area for further investigation within academia and industry. While existing literature has examined various aspects of XR technology, such as its applications, user experiences, and societal implications, there remains a notable absence of research focusing on specific dimensions, such as the intersection of XR with cultural contexts, the ethical considerations surrounding XR adoption, or the long-term effects of prolonged XR usage on human behavior and cognition [27]. Consequently, addressing these gaps enhances our understanding of XR's multifaceted impacts and informs the development of more nuanced approaches to its implementation and regulation [28]. In conclusion, bridging the research gap in extended reality topics holds significant promise for advancing scholarly discourse and guiding practical applications in this burgeoning field.

Based on the research gap analysis, it is evident that the topic of virtual reality (VR) is more predominant compared to extended reality (XR), thereby presenting an opportunity for further investigation. While VR has garnered considerable attention in academic literature and industry discourse, XR, encompassing a broader spectrum of immersive technologies, remains relatively underexplored [29], [30]. This discrepancy highlights an avenue for researchers to delve into XR's unique features, applications, and implications, filling the existing void in scholarly understanding [31]. Consequently, this research opportunity contributes to advancing knowledge in the field of extended reality and enriches interdisciplinary discussions on the evolving landscape of immersive technologies.

Subsequent studies on augmented reality (AR) are also gaining popularity, paralleling the interest in virtual reality (VR). AR, akin to VR, offers immersive experiences by overlaying digital content onto the physical environment, thus captivating scholarly and industry attention alike [32], [33]. The surge in research interest surrounding AR underscores its potential as a transformative technology with diverse applications across various domains, including education, healthcare, gaming, and retail [34]. Moreover, the parallels between AR and VR highlight the interconnectedness of immersive technologies and the need for comprehensive investigations into their respective impacts, challenges, and opportunities [35]. In conclusion, the burgeoning interest in augmented reality alongside virtual reality underscores the growing significance of immersive technologies in shaping contemporary digital experiences and warrants further exploration in scholarly research.

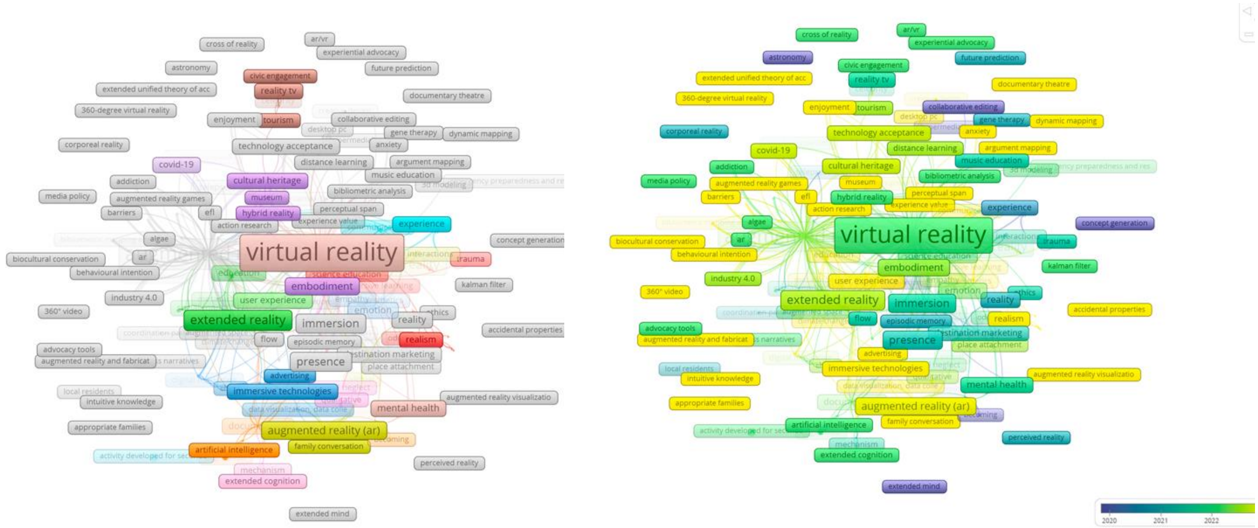

Figure 1. Gap Analysis using Vosviewer

Figure 1 shows the gap analysis using Vosviewer. The gap analysis results using Vosviewer indicate a need for enhanced focus on studies about extended reality (XR). While existing literature has provided valuable insights into various aspects of XR technology, such as its applications, implications, and adoption challenges, the analysis underscores a notable gap in the depth and breadth of research within this domain. This finding highlights the opportunity for scholars and researchers to delve deeper into the multifaceted dimensions of XR, exploring uncharted territories and addressing emerging issues. Consequently, prioritizing and expanding research efforts in extended reality enriches scholarly discourse and fosters innovation and advancements in this rapidly evolving field.

Considering these factors, this research aims to classify public sentiments and analyze social networks based on Extended Reality product content review data, with a case study focusing on the Apple Vision Pro. By undertaking this investigation, the study seeks to provide valuable insights into the perception and reception of XR products among consumers, elucidating patterns of sentiment expression and identifying critical influencers within social networks. Furthermore, utilizing a specific case study, such as the Apple Vision Pro, enables a nuanced examination of real-world applications and user experiences, contributing to a deeper understanding of the practical implications of extended reality technologies. In summary, this research endeavor holds promise for enriching scholarly discourse, informing industry practices, and guiding future developments in extended reality.

2.2 Cross-Industry Standard Process for Data Mining (CRISP-DM)

The approach employed in this research is the Cross-Industry Standard Process for Data Mining (CRISP-DM). CRISP-DM is a widely recognized methodology for guiding data mining projects, providing a structured framework comprising six phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. By adopting CRISP-DM, this study ensures a systematic and rigorous approach to data analysis, facilitating a comprehensive exploration of public sentiments and social network dynamics surrounding Extended Reality (XR) products. Furthermore, using CRISP-DM enhances the research findings' transparency, replicability, and validity, thereby bolstering the credibility and reliability of the study outcomes [36]–[38]. In summary, the application of CRISPR-DM in this research underscores the commitment to methodological rigor. It facilitates a robust investigation into the complexities of XR technology within the context of public sentiment analysis.

Through CRISP-DM, sentiment and social network analysis will be conducted to delve deeper into the perceptions and interactions surrounding Extended Reality (XR) products. This methodology enables the systematic examination of user-generated content and interactions on social media platforms, facilitating the identification of prevailing sentiments, key influencers, and network structures within online communities. By leveraging CRISP-DM for sentiment and social network analysis, this research aims to uncover valuable insights into the reception and dissemination of XR products, informing academic discourse and industry practices. In summary, the application of CRISP-DM in this context promises to offer a comprehensive understanding of public sentiment and social dynamics surrounding XR, contributing to advancing knowledge in this burgeoning field.

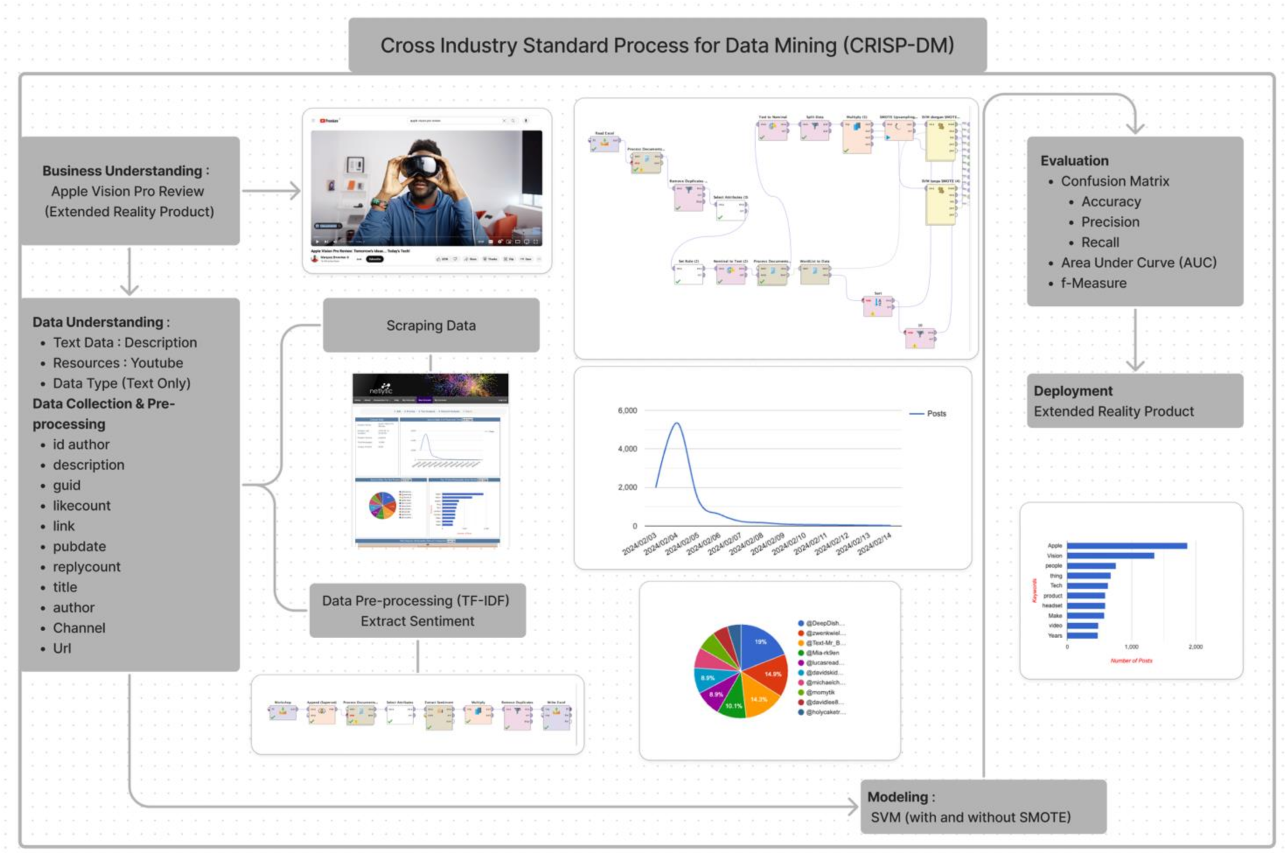

Figure 2. Implementation of CRISP-DM in Social Network Analysis and Sentiment Classification

Figure 2 shows the framework of CRISP-DM in social network analysis and sentiment classification. The Cross Industry Standard Process for Data Mining (CRISP-DM) framework stands out as a highly effective methodology for guiding the process of data mining and analytics projects. Its primary strength lies in its systematic approach, which encompasses six distinct phases: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. This structured framework facilitates a clear understanding of project objectives, ensures thorough data exploration and preparation, enables the development of accurate predictive models, and allows for rigorous evaluation and deployment of these models in real-world applications. Additionally, CRISP-DM promotes collaboration among stakeholders and interdisciplinary teams, fostering a holistic approach to data-driven decision-making. As such, CRISP-DM remains a preferred methodology in the field of data science and analytics, offering a comprehensive and systematic framework for addressing complex analytical challenges.

2.2.1 Business Understanding

In the business understanding phase, the discussion context revolves around the review data of the Apple Vision Pro video content (id = 86Gy035z_KA) with 12,044 comments. This initial phase of the CRISP-DM methodology entails clearly understanding the business objectives and requirements that frame the subsequent data analysis processes. Focusing on the specific Apple Vision Pro video content case allows a targeted investigation into public sentiments and social interactions surrounding this XR product. Furthermore, the substantial number of comments provides a rich dataset for in-depth analysis, offering valuable insights into consumer perceptions and engagement patterns. In summary, leveraging the review data from the Apple Vision Pro video content during the business understanding phase sets the foundation for a comprehensive examination of public sentiment and social network dynamics in extended reality products.

2.2.2 Data Understanding

In the data understanding phase, it is crucial to comprehend the data to be utilized in the sentiment classification and Social Network Analysis (SNA) processes. Data description will be extracted within sentiment classification to discern the underlying sentiments expressed within the review data. Conversely, the interactions among users within the review data will be scrutinized for Social Network Analysis to unveil network structures and influential nodes. This phase lays the groundwork for subsequent analyses by ensuring a thorough grasp of the dataset's characteristics and relevant attributes. Consequently, a comprehensive understanding of the data facilitates accurate interpretation and extraction of insights, thereby enhancing the validity and reliability of the research outcomes.

This research utilizes RapidMiner, employing the extract data operator to discern string scores for classifying negative and positive classes. RapidMiner, a robust data mining tool, enables efficient data preprocessing and analysis, facilitating extracting relevant information essential for sentiment classification. Researchers can effectively parse and analyze textual data by employing the extract data operator within RapidMiner, thereby identifying sentiment indicators and distinguishing between positive and negative sentiments expressed within the review dataset. This methodological approach underscores the research's commitment to utilizing advanced data mining techniques to derive meaningful insights from the collected data, enhancing the overall rigor and validity of the study outcomes.

Figure 3. Extract Sentiment Process in Rapidminer

Figure 3 shows the extract sentiment process in Rapidminer. Based on the extraction results, it is discernible that 1604 reviews are classified as harmful, and 8278 reviews are classified as positive. This quantitative breakdown provides valuable insights into the distribution of sentiments within the review dataset, facilitating a nuanced understanding of public perceptions towards the Apple Vision Pro product. The clear distinction between negative and positive classes underscores the significance of sentiment analysis in gauging consumer sentiment and informing strategic decision-making processes. In summary, delineating sentiment classes based on the extraction results is a foundational step in the sentiment classification process, laying the groundwork for subsequent analyses to elucidate patterns and trends within the dataset.

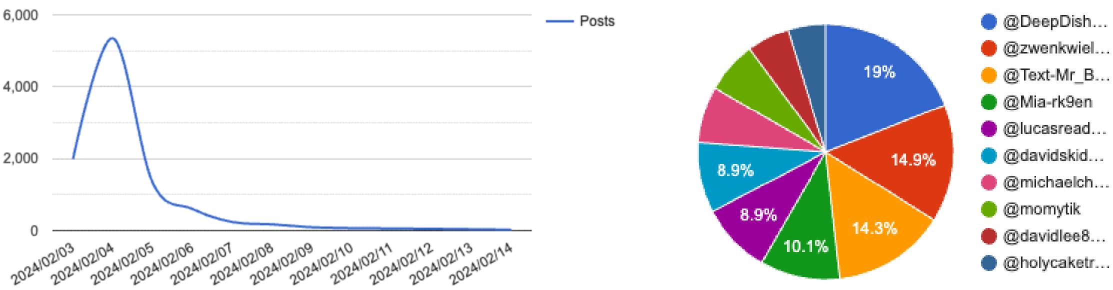

Figure 4. Post Over Time and Top Ten Poster of Extended Reality Product Review (Apple Vision Pro)

Figure 4 shows the post over time and top ten poster data. The analysis of data post over time and identification of top ten posters offers invaluable insights into the temporal dynamics and key contributors within a given dataset or online community. By tracking the evolution of posts over time, researchers can discern patterns, trends, and fluctuations in user activity, which may reflect changes in interests, engagement levels, or external factors influencing the community. Moreover, identifying the top ten posters provides visibility into the most active and influential members of the community, whose contributions may significantly impact discussions, information dissemination, and community dynamics. This information not only facilitates a deeper understanding of user behavior and engagement patterns but also enables researchers to target specific individuals for further analysis or engagement strategies. Ultimately, leveraging data post over time and top ten posters enhances the comprehensiveness and granularity of social network analysis, contributing to a more nuanced understanding of online communities and their dynamics.

2.2.3 Modeling

In the modeling phase, the performance of algorithms in sentiment classification based on positive and negative classes will be evaluated. This pivotal stage involves implementing and testing various machine learning and natural language processing techniques to ascertain their effectiveness in accurately classifying sentiments within the review dataset. By rigorously assessing the performance of these algorithms, researchers can identify the most suitable approach for sentiment classification, thereby enhancing the accuracy and reliability of the analytical outcomes. Consequently, the modeling phase serves as a critical component in refining the sentiment classification process, ultimately contributing to the robustness and validity of the research findings. The model utilized for classification in this study is the Support Vector Machine (SVM). SVM is a robust machine learning algorithm commonly employed for binary classification tasks, such as sentiment analysis. Its effectiveness lies in its ability to identify optimal hyperplanes that separate different classes within the dataset, thereby enabling accurate classification. SVM's versatility and robustness make it well-suited for analyzing textual data and discerning sentiment polarity. By leveraging SVM as the classification model, this research achieves precise and reliable sentiment classification outcomes, thereby enhancing the overall validity and robustness of the study findings. The regression function of the SVM method is as follows.

$$f(x) = w.x + b \tag{2}$$

Where :
$f(x)$ is the decision function,
W is the weight vector perpendicular to the hyperplane,
X is the input feature vector,
B is the bias term.

In the case of binary classification, the class label y_i of a data point x_i can be determined by the sign of $f(x)$:

$$y_i = \begin{cases} +1, \ if\ f(x_i) \ \geq 0 \\ -1, if\ f(x_i) \ < 1 \end{cases} \tag{3}$$

In non-linearly separable cases, SVM utilizes a kernel function $\mathrm{K}(x_i, x_j)$ to map the input feature vectors into a higher-dimensional space where the data becomes linearly separable. The decision function then becomes:

$$f(x) \ = \ \textstyle\sum_{i=1}^{N} \propto_i, y_j \ \mathrm{K}(x_i, x) + \mathrm{b} \tag{4}$$

Where $\propto_i$ are the Lagrange multipliers obtained during training. The accuracy, precision, recall, f-measure, and AUC of the confusion matrix values will be assessed in the evaluation phase. This critical stage involves quantifying the performance of the sentiment classification model by examining its ability to classify positive and negative sentiments correctly and identifying potential improvement areas [39]. The evaluation metrics provided by the confusion matrix offer comprehensive insights into the model's effectiveness in classification accuracy, precision, recall, and overall predictive performance [40]. By scrutinizing these metrics, researchers can gain a nuanced understanding of the model's strengths and weaknesses, enabling informed decisions regarding its refinement and optimization [41]. Thus, the evaluation phase plays a pivotal role in validating the efficacy and reliability of the sentiment classification model, thereby enhancing the credibility and robustness of the research outcomes.

This research also employs Social Network Analysis (SNA) to analyze actor networks within the review data. SNA offers a robust framework for examining the relationships and interactions among actors within a social network, providing insights into communication patterns, influence, and information flow. By applying SNA to the review dataset, this study aims to identify central actors, influential nodes, and community structures within the social network of consumers engaging with extended reality products. This analytical approach enhances our understanding of the social dynamics surrounding extended reality adoption and provides valuable insights into disseminating information and sentiments within online communities. In conclusion, leveraging SNA in this research facilitates a nuanced exploration of actor networks, contributing to a deeper understanding of the social dimensions shaping consumer perceptions and behaviors towards extended reality products.

$$[C = \frac{L}{N(N-1)}] \tag{1}$$

Where:
(C) is the connectivity coefficient
(L) is the number of links
(N) is the number of nodes

The objective of utilizing Social Network Analysis (SNA) before sentiment classification is to uncover underlying patterns and structures within the social network of actors engaging with extended reality products. By examining the interconnections among users and identifying influential nodes or communities, SNA provides valuable insights into information dissemination, influence propagation, and opinion formation within online communities. This preliminary analysis is a foundational step in understanding the review data's social context, informing subsequent sentiment classification processes. In essence, leveraging SNA before sentiment classification enhances the comprehensiveness and contextual understanding of the data, ultimately contributing to more accurate and nuanced sentiment analysis outcomes.

2.2.4 Evaluation

In the evaluation phase, the performance of algorithms is assessed based on several key metrics, including accuracy, precision, recall, f-measure, and Area Under the Curve (AUC). These metrics provide quantitative measures of the algorithms' effectiveness in sentiment classification tasks. Meanwhile, Social Network Analysis (SNA) undergoes evaluation based on network metrics such as density, reciprocity, centralization, modularity, and diameter. These metrics offer insights into the structural dynamics and interaction patterns within the network, thereby contributing to a comprehensive understanding of the social dynamics surrounding extended reality (XR) products. Through rigorous evaluation of both algorithms and SNA, this research aims to provide robust insights into consumer sentiments and social networks in the XR community.

2.2.5 Data Understanding

In the deployment phase, insights into consumer sentiments and perceptions regarding extended reality products and effective marketing strategies can be gleaned. This critical stage involves translating sentiment analysis and consumer behavior research findings into actionable recommendations for industry practitioners and marketers. By leveraging the insights from the analysis, companies can tailor their marketing strategies to better resonate with consumer preferences and effectively communicate the value proposition of extended reality products. Additionally, understanding consumer sentiments enables companies to address potential concerns or areas for improvement, thereby enhancing product adoption and customer satisfaction. Ultimately, the deployment phase serves as a crucial bridge between research findings and practical applications, facilitating informed decision-making and enhancing the overall effectiveness of marketing initiatives in the extended reality market.

3. RESULT AND DISCUSSION

This research employs the consumer behavior perspective to elucidate responses towards extended reality products. The primary focus of this approach is to analyze how consumers perceive, evaluate, and respond to the Apple Vision Pro and other extended reality products in the market. Utilizing the consumer behavior lens allows an in-depth exploration of factors influencing consumer decision-making, including attitudes, motivations, and preferences regarding extended reality technologies [42]. This perspective contributes to a comprehensive understanding of the dynamics shaping the adoption and acceptance of extended reality products, providing valuable insights for academics and industry practitioners [43], [44]. In conclusion, integrating the consumer behavior framework into the research design enriches the analysis, offering a holistic view of how individuals navigate and respond to the evolving landscape of extended reality products.

The popularity of Extended Reality (XR) through the Apple Vision Pro elicits pros and cons, as discerned from review video data. While some users admire the immersive experiences and innovative features offered by the product, others raise concerns regarding its usability, compatibility, or ethical implications [45]. This dichotomy of perspectives underscores the complex interplay between technological advancement and societal perceptions, highlighting the need for a nuanced understanding of the factors shaping public opinion towards XR products [46], [47]. By analyzing the sentiments and feedback expressed within the review data, researchers can gain valuable insights into the diverse viewpoints surrounding the Apple Vision Pro and inform future developments and strategies in the extended reality market.

Several key network metrics can be derived based on the Social Network Analysis (SNA) results. The network diameter, measuring the maximum distance between any pair of nodes, is 3, indicating relatively short paths of information dissemination within the network. Additionally, the density of the network, representing the proportion of observed connections to all possible connections, is calculated to be 0.000124, suggesting a sparse network structure. The absence of reciprocity, denoting the extent to which relationships are mutual, highlights a lack of node connections. Furthermore, the centralization value 0.001331 indicates a decentralized network structure, with no single node exerting significant influence. Lastly, the modularity value 0.999000 indicates a highly modular network characterized by distinct and tightly-knit communities. These SNA metrics offer valuable insights into the structural characteristics and dynamics of the network, informing strategic decisions and interventions aimed at enhancing network efficiency and connectivity.

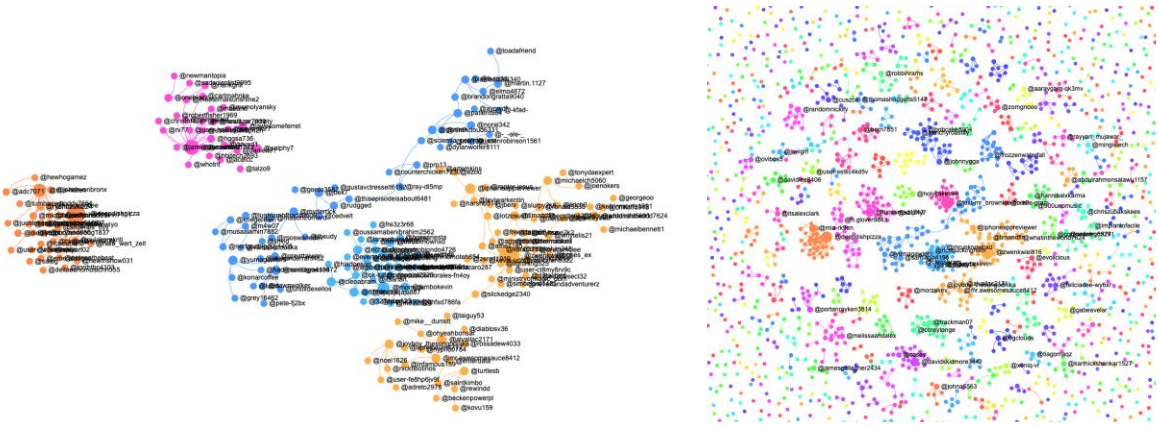

Figure 5. Chain Network "Who Replies to Whom"

Figure 5 shows the chain network of who replies to whom categories. From the perspective of an Extended Reality (XR) consumer, the SNA metrics provide valuable insights into the dynamics of information dissemination and interaction within the XR community. The relatively short network diameter suggests that information regarding XR products, such as the Apple Vision Pro, can spread quickly among consumers, facilitating rapid knowledge dissemination and awareness-building. However, the sparse network density implies that connections between XR consumers may be limited, potentially hindering community collaboration opportunities or collective action. The absence of reciprocity indicates that interactions among XR consumers may be predominantly one-sided, with limited mutual engagement or dialogue. Moreover, the decentralized network structure suggests that influence within the XR community is distributed across multiple nodes rather than concentrated in a few influential individuals or organizations. Lastly, the high modularity of the network suggests the presence of distinct and tightly-knit subgroups within the XR community, potentially representing different user segments or interest groups. Overall, from the perspective of an XR consumer, these SNA metrics highlight strengths and limitations within the XR community, informing strategies for enhancing connectivity, collaboration, and engagement among consumers.

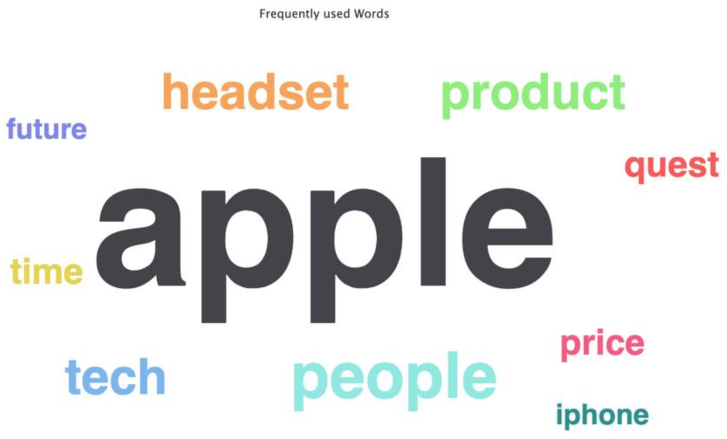

Figure 6. Frequently used Words

Figure 6 shows the frequently used words of the content reviews. Based on the results of identifying frequently used words, it is evident that specific terms prominently emerge within the discourse surrounding extended reality (XR) products, particularly the Apple Vision Pro. The analysis reveals that words such as "apple," "people," "tech," "headset," and "product" are among the most commonly occurring terms, with "apple" appearing 1870 times, "people" 756 times, "tech" 637 times, "headset" 587 times, and "product" 589 times, suggesting significant themes and topics of discussion within the XR community. Additionally, terms like "quest," "price," "time," "future," and "iPhone" also feature prominently, with "quest" appearing 439 times, "price" 457 times, "time" 449 times, "future" 443 times, and "iPhone" 343 times, indicating key considerations and interests among consumers regarding XR technologies. This identification of frequently used words provides valuable insights into the prevailing topics and sentiments within the discourse surrounding XR products, aiding in understanding consumer preferences and informing strategic decisions within the XR market landscape. The quantitative representation of these frequently used words underscores their relevance and prevalence in discussions related to XR, highlighting areas of focus and interest among consumers and industry stakeholders alike.

Analyzing frequently used words within the discourse surrounding extended reality (XR) products, such as the Apple Vision Pro, offers valuable insights into consumer behavior and preferences. The prominence of terms like "apple," "people," and "tech" suggests a strong association with the brand, indicating consumer interest in Apple's XR offerings. Additionally, terms like "headset" and "product" underscore consumers' focus on the tangible aspects of XR technology, indicating a desire for high-quality hardware and immersive experiences. Furthermore, terms like "price" and "iPhone" highlight consumers' considerations of affordability and compatibility with existing Apple devices, indicating potential barriers or facilitators to adoption. This analysis reflects consumers' interest in XR technology, their brand loyalty to Apple, and their practicality, affordability, and compatibility considerations when evaluating XR products. It provides valuable insights for XR product development and marketing strategies to meet consumer needs and preferences.

After identifying frequently used words, it is imperative to conduct an analysis based on the number of scores and scoring strings derived from sentiment extraction results. This additional analysis aims to deepen the understanding of sentiment patterns associated with the frequently used words, shedding light on the nuanced sentiments expressed by consumers in the context of extended reality products, particularly the Apple Vision Pro. Examining scores and scoring strings provides a quantitative perspective on the intensity and polarity of sentiments, allowing researchers to discern the prevalent sentiments and the variations and degrees of positivity or negativity associated with specific terms. This multifaceted analysis enhances the granularity of insights drawn from sentiment extraction, enabling a more nuanced interpretation of consumer sentiments and contributing to a comprehensive understanding of the intricacies within the review dataset. In summary, this dual-layered analysis approach, involving frequently used words and sentiment scores, enriches the research methodology, providing a more detailed and contextually rich exploration of consumer sentiments in the extended reality domain.

Table 1. Classification based on Extract Sentiment Result

Review	String Score	Score	Classification
If they want developers to make apps for them, they need to change their cut. I'm not falling into the trap of building for apple's ecosystem again. Fuck Apple and their shitty cut for devs. Also the install bullshit is also insane in the EU.	want (0.08) cut (-0.28) falling (-0.15) trap (-0.33) fuck (-0.64) shitty (-0.67) cut (-0.28) bullshit (-0.72) insane (-0.44)	-3,4358974358974	Negative
I think anything with apple, due to the ecosystem, people will want it. Like, for me, I was pretty against getting anything apple. It wasn't till I went back to school that I decided to buy apple products, due to the longevity of them and the seamless ecosystem that it creates. It is very useful for college student imo. Are the products perfect? No. Are there better options out there for each product? Yes. Do those better products connect effortlessly together for a pretty awesome experience? Absolutely not. So, I think the vision pro will be successful if the ecosystem allows it to be successful.	want (0.08) like (0.38) pretty (0.56) creates (0.28) useful (0.49) perfect (0.69) no (-0.31) better (0.49) yes (0.44) better (0.49) pretty (0.56) awesome (0.79) vision (0.26) successful (0.72) successful (0.72)	6,6410256410256 4	Positive

Table 1 shows the result of extract sentiment operator in Rapidminer. Based on the sentiment extraction results obtained through the RapidMiner application, it is evident that there are 8278 instances categorized as positive sentiments and 1604 instances categorized as negative sentiments. This classification is discernible from various indicators, including Sentiment, Score, Scoring String, Negativity, Positivity, Uncovered Tokens, and Total Tokens. These metrics provide comprehensive insights into the sentiment distribution within the dataset, enabling a detailed understanding of consumer perceptions towards the Apple Vision Pro and other extended reality products. The systematic extraction and analysis of sentiment indicators signify the methodological rigor employed in this research, enhancing the credibility and reliability of the sentiment classification outcomes. Thus, sentiment extraction is crucial in uncovering consumer sentiments and informing strategic decisions within the extended reality market landscape.

Subsequently, a performance analysis of the SVM algorithm is conducted, both with and without utilizing the SMOTE. This comparative analysis aims to evaluate the impact of employing SMOTE on the SVM model's performance in sentiment classification. SMOTE is particularly relevant in addressing imbalances within the dataset, enhancing the algorithm's ability to handle minority class instances. By comparing the results of SVM with and without SMOTE, researchers can discern the effectiveness of this oversampling technique in improving the model's accuracy, precision, recall, and overall performance in classifying positive and negative sentiments within the review dataset. This analytical approach contributes to a more comprehensive understanding of the trade-offs and benefits of employing SMOTE in sentiment analysis, informing decisions regarding optimal model configurations for handling imbalanced data. In conclusion, the analysis of SVM performance with and without SMOTE adds depth to the methodological framework, offering valuable insights into the nuances of sentiment classification within the context of extended reality product reviews.

Table 2. Confusion Matrix of SVM with and without SMOTE

Confusion Matrix	SVM with SMOTE	SVM without SMOTE
Accuracy	81.82%	84.33%
Precision	97.58%	84.67%
Recall	70.37%	99.28%
F-measure	81.77%	91.39%
AUC	0.951	0.790

Table 2 shows the confusion matrix of SVM with and without SMOTE. Based on the evaluation results of the SVM algorithm without employing the SMOTE, it is discernible that the model exhibits commendable performance metrics. The performance vector illustrates an accuracy of 84.33% with a micro average of the same value, indicating a high level of classification accuracy. Furthermore, the precision, recall, and f_measure metrics demonstrate robust performance, with precision at 84.67%, recall at 99.28%, and f_measure at 91.39%, all showcasing consistently high values. These results are reinforced by the Confusion Matrix, which showcases relatively balanced true negative and positive classifications. Moreover, the AUC values further confirm the model's effectiveness in distinguishing between positive and negative classes. In addition, the performance evaluation of the SVM algorithm with the SMOTE reveals notable performance metrics. The performance vector demonstrates an accuracy of 81.82%, with a micro average of the same value, indicating a satisfactory level of classification accuracy. However, it is notable that precision attains a higher value of 97.58%, suggesting a solid ability to classify positive instances correctly. Conversely, the recall metric yields a lower value of 70.37%, indicating a relatively lower ability to identify all positive instances correctly. The f_measure, which combines precision and recall, showcases a balanced performance with a value of 81.77%. Overall, while the SVM with SMOTE demonstrates satisfactory performance, particularly in precision, improvements in recall could enhance its effectiveness in accurately identifying positive instances.

SVM with SMOTE **SVM without SMOTE**

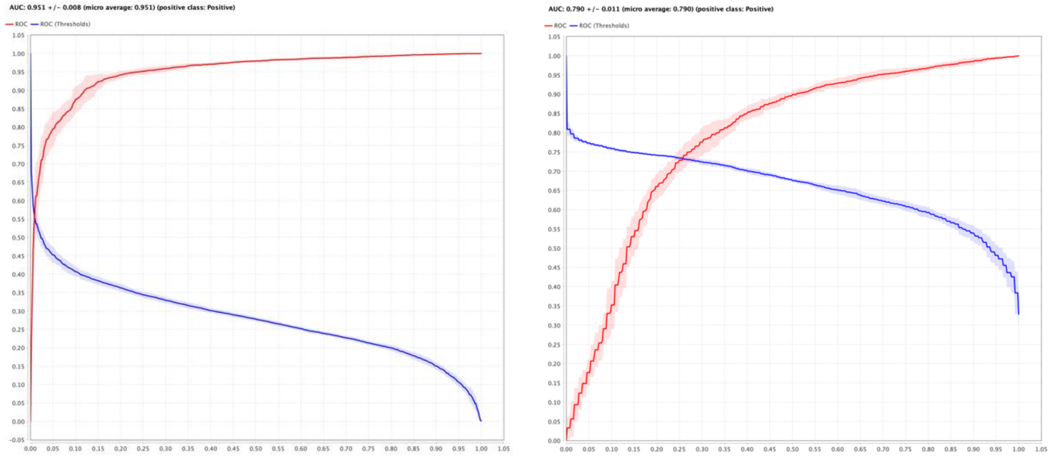

Figure 7. Area Under Curve

Figure 7 shows the AUC of SVM with and without SMOTE. The comparison between the SVM algorithm with and without the SMOTE highlights contrasting performance outcomes. Without employing SMOTE, the SVM algorithm achieved commendable performance metrics, with an accuracy of 84.33% and consistently high precision, recall, and f_measure values, indicating robust performance in sentiment classification tasks. The Confusion Matrix also depicted balanced true negative and positive classifications, affirming the model's effectiveness in distinguishing between sentiments. On the other hand, the SVM algorithm with SMOTE demonstrated satisfactory accuracy but showed discrepancies in precision and recall. While precision reached a notably high value, indicating a solid ability to classify positive instances accurately, recall yielded a lower value, suggesting challenges in identifying all positive instances correctly. The Confusion Matrix further emphasized a tendency towards negative classifications. Overall, the comparison underscores the trade-offs between accuracy, precision, and recall when employing oversampling techniques like SMOTE in sentiment analysis tasks, with implications for optimizing model performance in handling imbalanced datasets.

Sentiment classification results provide valuable insights into XR product consumer sentiment and its implications for XR technology. The analysis delves into the sentiments expressed by consumers towards XR products, shedding light on their perceptions and attitudes [48]. By examining sentiment patterns, researchers can discern consumer preferences, concerns, and overall satisfaction levels regarding the XR technology [49]. Furthermore, understanding consumer sentiment can inform strategic decision-making processes within the XR industry, guiding product development, marketing strategies, and user experience enhancements [50]. Analyzing sentiment classification results offers a nuanced understanding of consumer sentiment's role in shaping the trajectory of XR technology advancement. This research yields several recommendations to advance the understanding and application of extended reality (XR) technology. Firstly, there is a need for further exploration into consumer sentiment analysis methodologies to enhance the accuracy and efficiency of sentiment classification models, particularly in the XR domain. Additionally, leveraging social network analysis (SNA) alongside sentiment analysis could provide deeper insights into the dynamics of consumer interactions and influence within XR communities. Moreover, considering the rapid evolution of XR technology, continuous monitoring and adaptation of sentiment analysis techniques are essential to keep pace with changing consumer preferences and market trends. Ultimately, fostering interdisciplinary collaboration between researchers, industry practitioners, and policymakers can facilitate the development of comprehensive strategies to leverage consumer sentiment effectively in driving XR innovation and adoption.

4. CONCLUSION

In conclusion, this research offers valuable insights into consumer perceptions and social dynamics surrounding XR products, mainly focusing on the Apple Vision Pro. Applying sentiment analysis and Social Network Analysis (SNA) alongside methodologies such as CRISP-DM and SVM algorithms provides a comprehensive understanding of sentiment patterns, network structures, and influential factors within the XR community. The calculated network metrics reveal crucial aspects of network dynamics, including a density of 0.000124, absence of reciprocity, centralization value of 0.001331, and modularity value of 0.999000. Furthermore, analysis of frequently used words such as "apple" (1870 occurrences), "people" (756 occurrences), "tech" (637 occurrences), "headset" (587 occurrences), "product" (589 occurrences), "quest" (439 occurrences), "price" (457 occurrences), "time" (449 occurrences), "future" (443 occurrences), and "iPhone" (343 occurrences) sheds light on prevalent topics within the XR discourse. Additionally, the SVM algorithm without SMOTE achieves an accuracy rate of 84.33%, precision of 84.67%, recall of 99.28%, and f_measure of 91.39%, while the SVM with SMOTE exhibits an accuracy of 81.82% and precision of 97.58%. However, the latter sees a decline in recall to 70.37%. These findings inform strategic decisions and contribute to advancements in XR, offering insights into the trade-offs associated with oversampling techniques in sentiment analysis.

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