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Implementation of the GloVe in Topic Analysis based on Vader and TextBlob Sentiment Classification

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Abstract−This research investigates public sentiment towards tourism and gastronomy content through sentiment classification methodologies, employing the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework. Gastronomy plays a pivotal role in promoting culinary tourism rooted in cultural heritage. Food influencers significantly introduce cultural heritage through culinary expressions across various social media platforms and similar mediums. Leveraging sentiment analysis techniques, including Vader and TextBlob, the study analyzes a dataset of textual content related to tourism and gastronomy to discern prevailing sentiment distributions. The findings reveal a predominant prevalence of positive sentiments (72.19%), followed by neutral (23.33%) and negative sentiments (4.48%). These results shed light on the overall sentiment dynamics surrounding tourism and gastronomy content, indicating a predominantly positive reception among users. The study contributes to the body of knowledge in sentiment analysis research, particularly within tourism and gastronomy studies, offering valuable insights into user perceptions and attitudes. Such findings have implications for content creators, marketers, and policymakers seeking to enhance tourism and gastronomy experiences. Future research could delve deeper into the factors influencing sentiment expressions and explore strategies to leverage positive sentiments for promoting and advancing tourism and gastronomy endeavors within the CRISP-DM framework.

Keywords: Gastronomy; Culiner; Tourism; GloVe; Topic Modeling; Sentiment Classification

1. INTRODUCTION

Gastronomy plays a pivotal role in promoting culinary tourism rooted in cultural heritage. The intricate interplay of culinary traditions and cultural heritage fosters a unique gastronomic landscape, captivating tourists seeking authentic experiences [1]–[4]. Through preserving and celebrating indigenous recipes, cooking techniques, and culinary rituals, gastronomy serves as a conduit for transmitting cultural narratives across generations, enriching the tourism experience with depth and authenticity [5]–[8]. Furthermore, culinary tourism stimulates local economies, fosters cultural exchange, and enhances cross-cultural understanding [9]–[12]. In conclusion, gastronomy is a linchpin in promoting culinary tourism intertwined with cultural heritage, fostering economic growth and cultural appreciation within destination locales [13]–[16].

Food influencers significantly introduce cultural heritage through culinary expressions across various social media platforms and similar mediums. Food influencers are cultural ambassadors through their curated content and engaged audiences, spotlighting traditional dishes, cooking methods, and dining customs [17], [18]. Their platforms amplify the visibility of culinary traditions, making them accessible to global audiences and sparking interest in cultural exploration [10], [19], [20]. Food influencers often collaborate with local artisans, chefs, and cultural institutions, fostering community engagement and preservation efforts [21], [22]. In essence, the influence wielded by food influencers transcends mere gastronomic appreciation, catalyzing cultural exchange and preservation in the digital age.

The urgency of this research lies in identifying crucial topics within culinary content reviews based on sentiment classification, hence employing the GloVe model in topic modeling. By systematically categorizing sentiments associated with culinary discussions, this research aims to discern themes and sentiments prevalent in food-related discourse [23], [24]. Leveraging the GloVe model, renowned for its proficiency in semantic understanding, ensures a nuanced exploration of topics, facilitating a comprehensive understanding of the sentiments embedded within culinary content [21], [25]. Consequently, this approach enables a more informed analysis of culinary trends, preferences, and perceptions, thus enhancing consumer insights and strategic decision-making within the culinary domain.

The method proposed in this research is CRISP-DM (Cross-Industry Standard Process for Data Mining), a systematic approach widely utilized in data mining projects. CRISP-DM provides a structured framework encompassing six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. By adhering to CRISP-DM, this research systematically navigates the complexities of data analysis, ensuring a methodical and efficient process from data collection to model deployment. This methodological rigor facilitates reproducibility, scalability, and robustness in research endeavors, ultimately enhancing the reliability and validity of research outcomes [26]–[29]. Hence, adopting CRISP-DM is a cornerstone in facilitating rigorous and effective data-driven research practices.

Theoretical and practical implications abound in implementing the Global Vectors for Word Representation (GloVe) model in topic modeling for gastronomy, based on Vader sentiment classification. By leveraging GloVe's semantic understanding and Vader's sentiment analysis, this research delves into culinary discourse with unparalleled

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depth and precision, unveiling intricate patterns and sentiments embedded within gastronomic discussions. Integrating these advanced techniques enhances the accuracy and granularity of topic modeling in gastronomy and opens avenues for deeper exploration into consumer preferences, culinary trends, and cultural perceptions. Consequently, this holistic approach fosters a more nuanced understanding of gastronomic landscapes, enriching theoretical frameworks and practical applications in culinary research and industry practices.

Similar research in sentiment classification and topic modeling within the domains of tourism and gastronomy demonstrates a growing recognition of the importance of understanding consumer perceptions and preferences. These studies often employ natural language processing techniques to analyze textual data from online reviews, social media platforms, and other sources to uncover insights into tourist experiences and culinary trends [15], [23], [30]–[32]. However, limitations persist, including challenges related to data preprocessing, linguistic nuances, and the dynamic nature of online content. Despite these constraints, pursuing advanced methodologies and interdisciplinary approaches holds promise for overcoming such limitations, thereby advancing our understanding of the intricate interplay between sentiment, topics, and consumer behavior in tourism and gastronomy.

The contribution of this research to knowledge is substantial, as it pioneers the integration of advanced natural language processing techniques, specifically the Global Vectors for Word Representation (GloVe) model and Vader sentiment classification, in the domain of gastronomy topic modeling. By leveraging these sophisticated methodologies, this research extends the boundaries of culinary discourse analysis, offering more profound insights into the interplay between topics and sentiments within gastronomic discussions. Furthermore, this research fosters a more comprehensive understanding of culinary preferences, trends, and cultural perceptions, enriching theoretical frameworks and practical applications in gastronomy research and industry practices. In conclusion, this research significantly advances the field by providing novel methodologies and insights that contribute to broader gastronomy and computational linguistics knowledge.

2. RESEARCH METHODOLOGY

2.1 Gap Analysis of Tourism and Gastronomy through the Content of Food Influencer

This research meticulously analyzes gaps within tourism, gastronomy, food influencers, topic modeling, and sentiment classification, reflecting a comprehensive examination of the intersectionality between these fields. By scrutinizing the existing literature and methodologies employed in each domain, this study identifies areas where current research falls short in capturing the complexities inherent in gastronomic discourse and its influence on tourism. The research aims to bridge these gaps through this analysis by proposing novel methodologies and insights that contribute to a more holistic understanding of the dynamics between tourism, gastronomy, food influencers, and computational linguistics. Consequently, this research fills existing voids in the literature and sets a foundation for future studies to explore these interrelated topics more comprehensively.

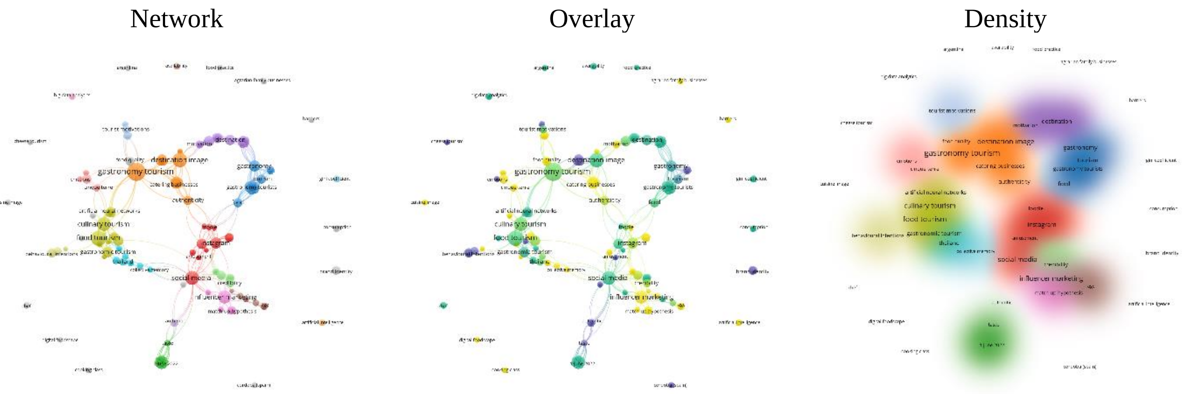

Figure 1. Network, Overlay, and Density of Tourism and Gastronomy Topics (VosViewer)

Based on the gap analysis results, it is evident that further investigation into topic modeling and sentiment classification within the field of gastronomy is warranted to analyze public sentiment and significant topics related to culinary, tourism, and gastronomy. This research gains more profound insights into the intricate interplay between gastronomic discourse, consumer perceptions, and tourism dynamics by delving into these methodologies. This analytical approach enhances our understanding of the multifaceted nature of gastronomic discussions and offers valuable implications for industry stakeholders, policymakers, and researchers alike. Consequently, conducting such studies is imperative to fill existing knowledge gaps and advance scholarship in gastronomy and related disciplines.

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

The method utilized in this research is CRISP-DM (Cross-Industry Standard Process for Data Mining), a structured approach widely employed in data mining projects. CRISP-DM encompasses several phases: Business Understanding,

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Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment. By adhering to CRISP-DM, this research systematically navigates the intricacies of data analysis, ensuring a methodical and efficient process from data collection to model deployment. This methodological rigor enhances reproducibility, scalability, and robustness in research endeavors, ultimately bolstering the reliability and validity of research outcomes. Thus, adopting CRISP-DM is a cornerstone in facilitating rigorous and effective data-driven research practices.

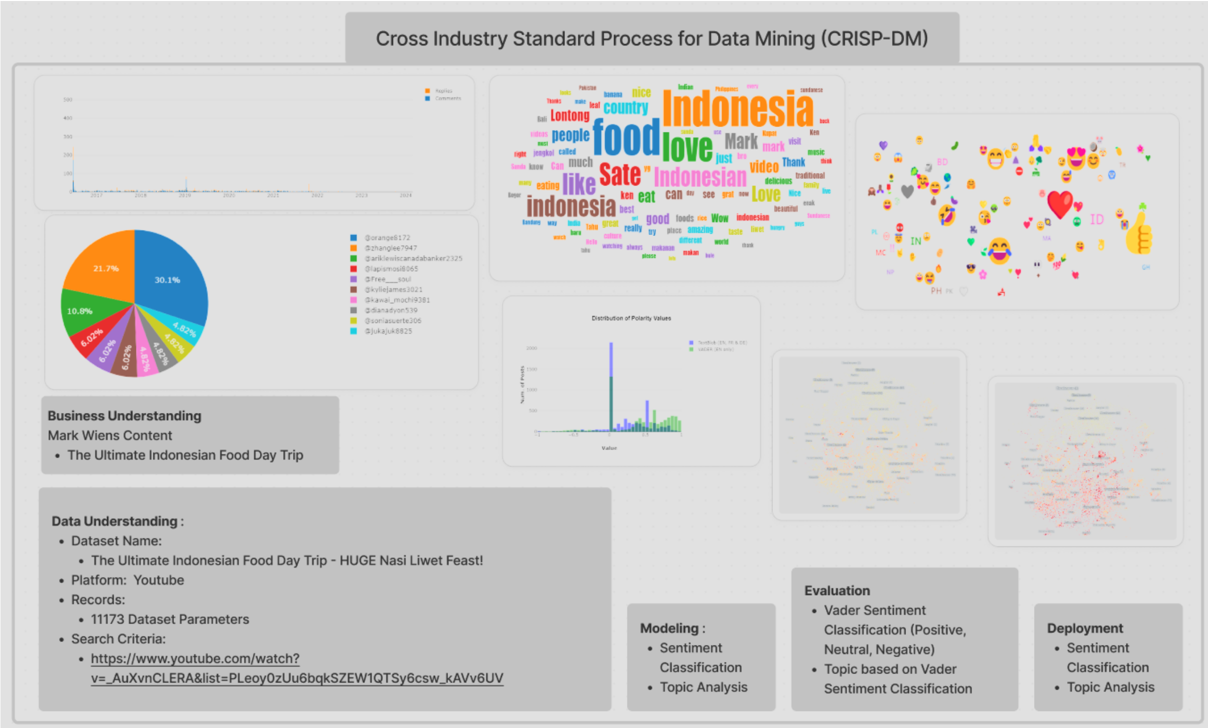

Figure 2. CRISP-DM Framework

Figure 2 shows the CRISP-DM framework. The CRISP-DM methodology involves Sentiment Classification and Topic Modeling, which play integral roles in extracting insights from textual data. Sentiment Classification aims to categorize the sentiment expressed in text data into positive, negative, or neutral categories, providing valuable insights into public perception and opinion. Meanwhile, Topic Modeling identifies prevalent themes or topics within the textual data, facilitating a deeper understanding of the underlying patterns and discussions. This dual approach allows researchers to unravel the complexities embedded within textual data, enabling comprehensive analyses that contribute to a richer understanding of the subject matter. Hence, integrating Sentiment Classification and Topic Modeling within the CRISP-DM framework enhances the depth and breadth of data analysis, ultimately leading to more robust research outcomes.

2.2.1 Business Understanding

During the business understanding phase, the focus of the discussion centers on the interplay between tourism and gastronomy, mediated by food influencers through video content disseminated on YouTube. This phase involves identifying the key objectives and requirements of the research project, which, in this case, revolve around understanding how food influencers leverage online platforms to promote gastronomic experiences and influence tourist behaviors. By delving into this context, this research gains insights into the dynamics between gastronomic content, influencer marketing, and tourism trends, laying a solid foundation for subsequent stages of the CRISP-DM methodology. Thus, the business understanding phase is a crucial starting point for framing the research objectives and guiding the data mining process toward achieving meaningful outcomes.

The videos utilized in this research constitute content created by the food influencer channel Mark Wiens, boasting a substantial subscriber base of 10.4 million. Specifically, the research draws upon videos accessible via the following id:_AuXvnCLERA&list=PLeoy0zUu6bqkSZEW1QTSy6csw_kAVv6UV. Mark Wiens' channel offers a wealth of gastronomic content, showcasing culinary experiences from diverse locales worldwide, thereby providing rich and varied material for analysis. Leveraging content from such a prominent influencer channel enhances the research's comprehensiveness and relevance within gastronomy and influencer marketing. Consequently, including Mark Wiens' videos strengthens the research's capacity to glean valuable insights into the interplay between food influencers, gastronomy, and tourist engagement.

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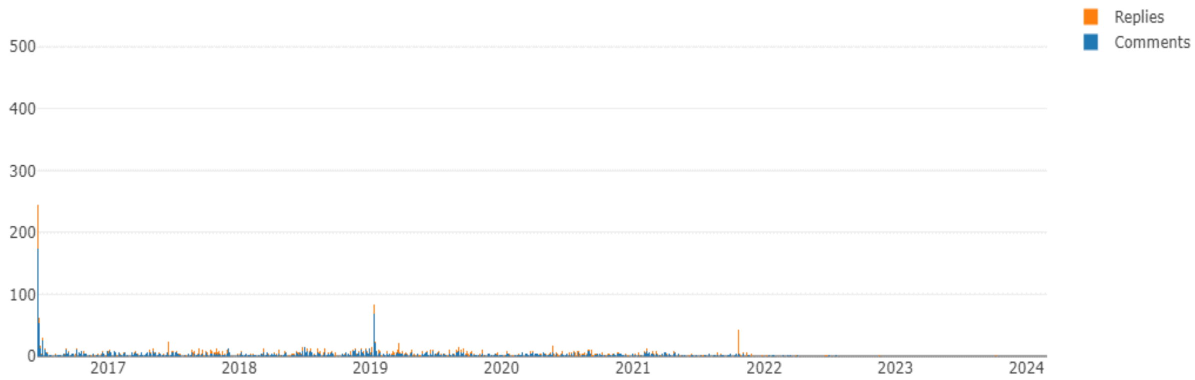

Figure 3. Post-per-day Statistic of the Video (Communalytic)

Figure 3 shows the post-per-day statistic of the content. Based on the post-per-day statistics provided, it is evident that there has been a fluctuation in the frequency of posts over the specified period. The data indicates that on June 19, 2016, there were 371 posts, followed by a decrease to 180 posts on the same day. Subsequently, there is a noticeable decline in the number of posts over the subsequent days, with figures dropping to 174, 111, and 43 posts on June 20th, 21st, and 22nd, respectively, along with corresponding decreases in subsequent posts per day. This variation in posting frequency may reflect changes in user engagement, content strategy, or external factors influencing posting behavior. Therefore, a closer examination of these trends could provide valuable insights into user interaction patterns and content dissemination strategies.

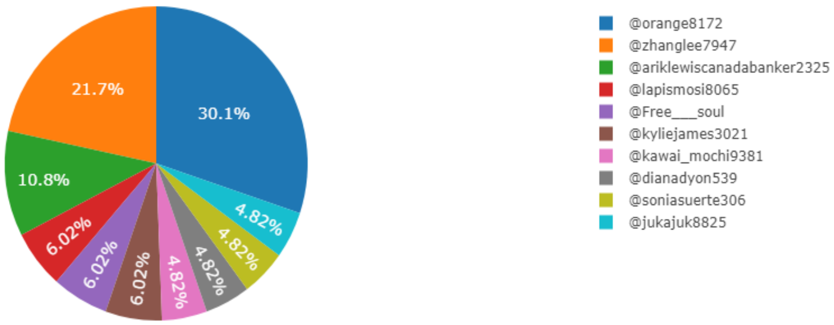

Figure 4. Top Ten Poster (Communalytic)

Figure 4 shows the top ten posters of the video. Based on the data regarding the top ten posters, there is apparent significant variance in the number of posts contributed by each user. The user @orange8172 stands out as the most prolific poster with 25 posts, followed by @zhanglee7947 with 18 posts and @ariklewiscanadabanker2325 with nine posts. Subsequently, there is a gradual decrease in the number of posts among the remaining users, with @lapismosi8065, @Free___soul, and @kyliejames3021 each contributing five posts, followed by several users with four posts each. This distribution underscores the unequal distribution of posting activity among users, which may reflect varying levels of engagement, interests, or motivations for participation. Further analysis of user behavior and motivations could provide valuable insights into community dynamics and interaction patterns within the platform.

Thus, audience sentiment towards food influencer video content is discerned from the perspectives of tourism and gastronomy through topic modeling and sentiment classification. By employing these analytical techniques, this research uncovers underlying themes and sentiments within the videos, providing valuable insights into the impact of gastronomic content on viewer perceptions and behaviors related to tourism. This holistic approach allows for a nuanced understanding of how food influencer content contributes to promoting culinary experiences and tourism destinations, thereby enhancing the effectiveness of marketing strategies and engagement efforts in the gastronomic domain. Consequently, integrating topic modeling and sentiment classification offers a comprehensive framework for analyzing audience sentiment and its implications for tourism and gastronomy.

2.2.2 Data Understanding

During the data understanding phase, frequently used words from content reviews are identified, facilitating a deeper comprehension of the textual data's characteristics and nuances. This process involves analyzing the frequency distribution of words across the dataset; this research identifies recurring terms or themes that may hold significance in the study context. By uncovering these frequently used words, this research gains insights into the prevalent topics, sentiments, and language patterns within the dataset, laying the groundwork for subsequent analyses in the research process. Consequently, this step is essential for establishing a comprehensive understanding of the data and informing further investigation into the research objectives.

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Figure 5. Frequently Used Words (Communalytic)

Figure 5 shows the word clouds. Based on the identification of frequently used words, it is evident that specific terms are recurrent within the dataset, providing insights into prevalent themes and topics. The analysis reveals that "food" occurs 100 times, followed closely by "Indonesia" with 99 occurrences, indicating a strong association with Indonesian cuisine and gastronomy. Additionally, terms such as "love" (78 occurrences) and "Sate" (59 occurrences) suggest a positive sentiment towards Indonesian food and culture. Furthermore, the inclusion of specific food items like "Lontong" (28 occurrences) and "State" highlights the significance of traditional Indonesian dishes in the discourse. This analysis underscores the importance of these terms in shaping perceptions and discussions surrounding Indonesian gastronomy, thereby informing further investigation into the interplay between food, culture, and tourism in Indonesia.

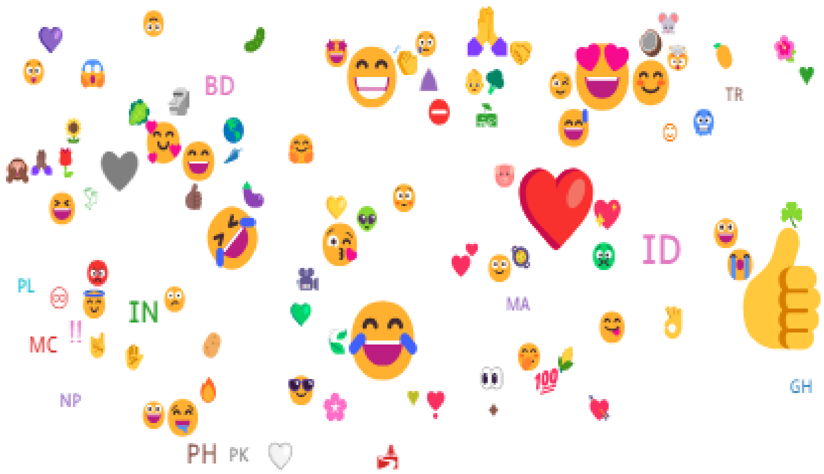

Figure 6. Emoji Cloud (Communalytic)

Figure 6 shows the emoji cloud. Based on the results of identifying emojis from the dataset, it is discernible that certain emojis are frequently used, indicating their significance in expressing sentiments and reactions within the content. The analysis reveals that the thumbs-up emoji (👍) is the most prevalent, appearing 42 times, followed by the heart emoji (❤️) with 30 occurrences, suggesting positive sentiments and approval from the audience. Additionally, emojis such as 😂, 😍, and 😁, each with significant occurrences, denote expressions of amusement, adoration, and happiness, respectively. Furthermore, the flag emoji (ID) highlights national pride or references to Indonesia. This analysis underscores the importance of emojis as non-verbal cues in conveying emotions and attitudes within digital content, enriching the understanding of audience engagement and sentiment in online discussions.

Based on the data understanding phase, the analysis and discussion are tailored to accommodate the characteristics of the data processed during the modeling stage. Understanding the nuances of the dataset, including patterns, trends, and prevalent themes, enables this research to devise appropriate modeling techniques and methodologies that effectively capture the underlying structures and insights within the data. By aligning the analysis

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and discussion with the dataset's specific attributes, this research ensures that their findings are relevant, accurate, and reflective of the complexities inherent in the data. Consequently, this approach facilitates a more robust and meaningful interpretation of the research outcomes, enhancing the overall quality and validity of the study.

2.2.3 Modeling

During the modeling stage, the data of reviews is classified based on sentiment using both the Vader and TextBlob approaches. This process involves leveraging computational algorithms to analyze the textual data and assign sentiment scores, enabling the categorization of reviews into positive, negative, or neutral sentiments. This research mitigates the limitations of individual methods by employing multiple sentiment analysis techniques such as Vader and TextBlob. It gains a more comprehensive understanding of the sentiments expressed within the dataset. Consequently, this dual approach enhances the accuracy and robustness of sentiment classification, thereby facilitating more nuanced insights into consumer perceptions and attitudes towards the subject matter.

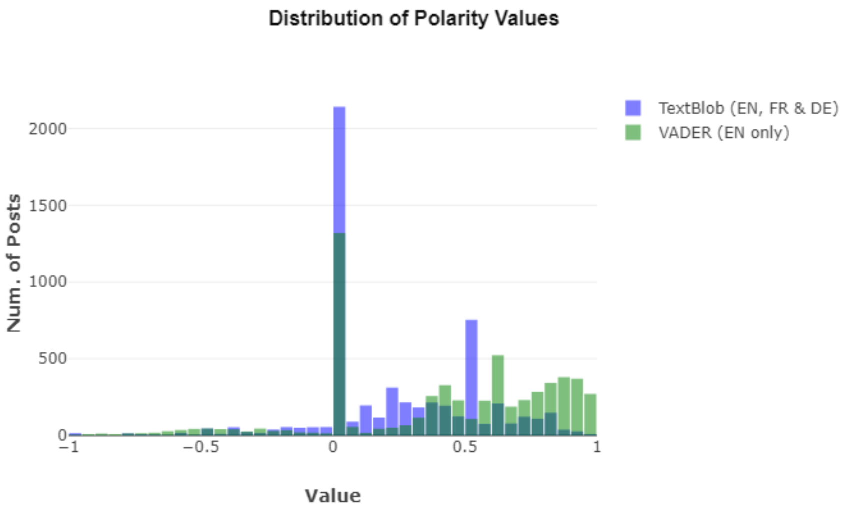

Figure 7. Vader and TextBlob Sentiment Classification (Communalytic)

Figure 7 shows the Vader and textblob sentiment classification model. This study utilizes 6058 out of 11173 posts to implement Vader and TextBlob, indicating a substantial portion of the analyzed dataset. The breakdown of sentiment analysis results reveals that Vader classified 5914 posts, with 492 (8.32%) categorized as unfavorable, 1333 (22.54%) as neutral, and 4089 (69.14%) as positive. Similarly, TextBlob processed the same number of posts, categorizing 5914 of them, with 428 (7.24%) identified as negative, 2053 (34.71%) as neutral, and 3433 (58.05%) as positive. This comprehensive analysis underscores the effectiveness of both Vader and TextBlob in discerning sentiments within the dataset, providing valuable insights into public perceptions and attitudes towards the subject matter.

Subsequently, the modeling process is conducted based on the topics most frequently discussed by content reviewers using GloVe embeddings. This approach involves utilizing the GloVe model, renowned for capturing semantic relationships between words and identifying prevalent themes and topics within the dataset. By leveraging GloVe embeddings, this research gains a deeper understanding of the underlying structures and patterns in the textual data, enabling the extraction of meaningful insights. This methodological approach enhances the effectiveness and efficiency of topic modeling, ultimately facilitating a more nuanced analysis of the subject matter. Consequently, employing GloVe embeddings in the modeling process enriches the research outcomes and contributes to a deeper understanding of the content reviewed by users.

2.2.4 Evaluation

During the evaluation stage, an investigation is conducted into the performance of the Vader and TextBlob models in sentiment classification. This process involves assessing each model's accuracy, precision, recall, and F1 score to determine their effectiveness in categorizing sentiments within the dataset. By comparing the performance metrics of Vader and TextBlob, this research ascertains the strengths and weaknesses of each model, informing decisions regarding their suitability for sentiment analysis tasks. Consequently, this evaluation phase plays a pivotal role in gauging the reliability and robustness of sentiment classification methodologies, ultimately guiding the selection of the most appropriate approach for subsequent analyses.

Subsequently, an evaluation of the performance of the GloVe model in topic analysis is conducted, aiming to assess its effectiveness in extracting meaningful topics from the dataset. This evaluation involves measures such as topic coherence, semantic similarity, and interpretability of the topics generated by the GloVe model. By analyzing these metrics, this research determines the quality and relevance of the topics identified, thereby gauging the suitability of the GloVe model for topic modeling tasks. Consequently, this evaluation phase serves as a critical step in validating

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the efficacy of the GloVe model in uncovering latent structures and insights within textual data, thus informing its utility in subsequent analytical endeavors.

2.2.5 Deployment

The deployment phase of the research findings on sentiment classification and topic modeling for tourism and gastronomy through food influencer content analysis involves disseminating the outcomes to relevant stakeholders and implementing the insights gained from the study into practical applications. This stage includes presenting the research findings through academic publications, conferences, and industry seminars and sharing the results with tourism boards, gastronomy associations, and digital marketing agencies. Furthermore, the deployment phase integrates research findings into decision-making processes within the tourism and hospitality sectors, fostering informed strategies and initiatives that capitalize on the identified sentiments and topics within food influencer content. Consequently, this phase is crucial in bridging the gap between academic research and real-world applications, driving positive advancements in tourism, gastronomy, and digital marketing.

3. RESULT AND DISCUSSION

The discussion in this research is divided into two main parts: sentiment classification and topic modeling based on GloVe embeddings. The first part focuses on analyzing and categorizing sentiments expressed in textual data, employing techniques such as Vader and TextBlob to classify sentiments as positive, negative, or neutral. The second part revolves around utilizing the GloVe model to extract latent topics and semantic structures from the textual data, facilitating a deeper understanding of the underlying themes and patterns. By partitioning the discussion into these two components, this research systematically explores and elucidates the complexities inherent in sentiment analysis and topic modeling, thereby enriching the understanding of the subject matter and contributing to advancements in computational linguistics and natural language processing methodologies.

3.1 Sentiment Classificaiton

Based on the results of sentiment classification, it is evident that VADER and TextBlob models demonstrate varying performances across different languages. In the English language sentiment classification, VADER categorized 5914 posts, with 492 (8.32%) identified as negative, 1333 (22.54%) as neutral, and 4089 (69.14%) as positive, while TextBlob classified a similar number of posts, with 428 (7.24%) negative, 2053 (34.71%) neutral, and 3433 (58.05%) positive. Interestingly, TextBlob's performance in French and German sentiment classification showcases nuanced differences, with French sentiment analysis displaying a higher percentage of neutral sentiments (94.38%) and German sentiment analysis achieving a remarkable 98.11% positive sentiment rate. These findings underscore the importance of considering linguistic nuances and language-specific models when conducting sentiment analysis, highlighting the need for tailored approaches to effectively capture sentiment across diverse linguistic contexts.

	# of Posts	Negative Sentiment [-1..-0.05]	Neutral Sentiment (-0.05..0.05)	Positive Sentiment [0.05..1]
VADER (English/EN)	5914	492 (8.32%)	1333 (22.54%)	4089 (69.14%)
TextBlob (English/EN)	5914	428 (7.24%)	2053 (34.71%)	3433 (58.05%)
TextBlob (French/FR)	89	1 (1.12%)	84 (94.38%)	4 (4.49%)
TextBlob (German/DE)	53	1 (1.89%)	52 (98.11%)	0 (0.00%)

Figure 8. Sentiment Classification (Communalytic)

Figure 8 shows the result of sentiment classification based on Vader and Textblob. Based on the results obtained from the application of Vader and TextBlob, it is evident that sentiment analysis revealed distinct distributions of sentiment polarity scores within the dataset. Specifically, the analysis identified 189 posts, constituting 4.48% of the dataset, with negative sentiments characterized by polarity scores less than or equal to -0.05. Additionally, 985 posts, representing 23.33% of the dataset, exhibited neutral sentiments, with polarity scores falling between -0.05 and 0.05. Most posts, totaling 3048 (72.19%), demonstrated positive sentiments, as indicated by polarity scores greater than or equal to 0.05. These findings illuminate the nuanced nature of sentiment expression within the dataset, underscoring the importance of employing multiple sentiment analysis tools to capture the diverse range of sentiments in textual data.

Based on the results of the sentiment analysis, it is discernible that a positive response exists towards tourism and gastronomic content disseminated by food influencers on the YouTube platform. This observation is substantiated by the prevalence of positive sentiment expressions within the analyzed dataset, indicating favorable perceptions and

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attitudes toward the subject matter. Additionally, positive sentiment sentiments suggest a decisive engagement and appreciation from the audience towards the content produced by food influencers, underscoring the influential role of digital platforms in shaping consumer preferences and perceptions in tourism and gastronomy. Consequently, these findings highlight the effectiveness of leveraging food influencers on YouTube to promote and popularize tourism and gastronomy-related content, fostering positive engagement and interaction among viewers.

3.2 Topic Analysis

Based on the results of sentiment classification, further modeling of topics was conducted using GloVe embeddings. This approach leverages the semantic relationships the GloVe model captures to extract latent topics and thematic structures within the dataset. By integrating sentiment analysis with topic modeling techniques, this research gains a deeper understanding of the underlying themes and sentiments expressed in the textual data, thereby facilitating comprehensive insights into the subject matter. Consequently, employing GloVe embeddings for topic modeling following sentiment classification enhances the depth and breadth of analysis, contributing to a more nuanced understanding of the sentiments and topics prevalent in the domain under investigation.

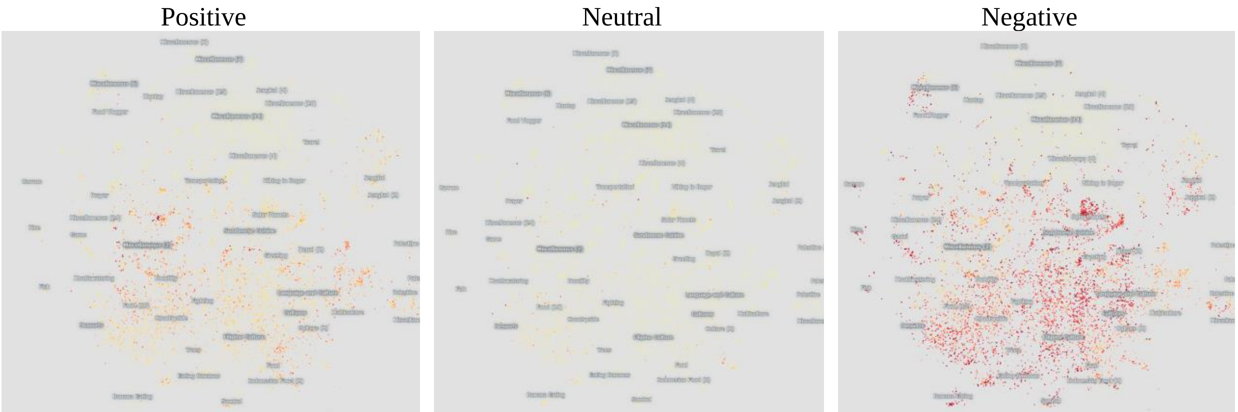

Figure 9. Topic Analysis based on Sentiment Classification (Communalytic)

Based on the visualization of topic analysis derived from sentiment classification, it becomes evident that users' sentiments are associated with more specific topics addressed in the videos. This visualization aids in identifying the nuanced sentiments expressed by users towards particular topics discussed or portrayed in the videos, thereby enabling a deeper understanding of user preferences, opinions, and reactions. Consequently, integrating sentiment classification with topic analysis facilitates a comprehensive exploration of user sentiment dynamics within specific thematic elements, contributing to informed decision-making and content optimization strategies in digital media platforms.

Using topic analysis based on GloVe embeddings offers significant benefits for content creators, particularly food influencers and stakeholders in the tourism and gastronomy sectors. By employing GloVe embeddings, topic analysis enables a nuanced exploration of thematic elements within textual content, facilitating the identification of trending topics, emerging trends, and audience preferences. This in-depth understanding empowers food influencers to tailor their content to align with audience interests, enhancing engagement and viewership. Moreover, for stakeholders in tourism and gastronomy, such analysis provides valuable insights into consumer preferences, enabling the development of targeted marketing strategies, product offerings, and destination promotion campaigns. Consequently, integrating GloVe-based topic analysis is valuable for content optimization and strategic decision-making, fostering enhanced audience engagement and industry growth.

3.3 Discussion

Gastronomy plays a pivotal role in advancing culturally-based culinary tourism in Indonesia. With its rich tapestry of diverse cultures and culinary traditions, Indonesia's gastronomic landscape serves as a beacon for tourists seeking authentic and immersive culinary experiences. By promoting and preserving indigenous culinary practices, such as traditional cooking methods, unique ingredients, and regional specialties, gastronomy fosters a deep appreciation for Indonesia's cultural heritage among domestic and international visitors. Furthermore, by showcasing the intricate interplay between food, culture, and history, gastronomic tourism contributes to economic growth, sustainable development, and cultural exchange, thereby solidifying its indispensable position in Indonesia's tourism industry.

Food influencers play a crucial role in introducing the flavors of Indonesian cuisine to international tourists and highlighting the unique cultural heritage of the archipelago. Food influencers showcase the diverse array of traditional Indonesian dishes, exotic ingredients, and culinary techniques to a global audience through their digital platforms and social media presence. By curating engaging content that celebrates the richness and authenticity of Indonesian gastronomy, these influencers effectively promote culinary tourism and facilitate cultural exchange. Moreover, their influence extends beyond mere gastronomic exploration, as they contribute to fostering appreciation for Indonesia's cultural diversity and heritage, thereby enhancing the country's appeal as a destination for cultural immersion and culinary exploration.

Based on the sentiment analysis results, it is evident that there is a substantial volume of positive responses towards gastronomy content in Indonesia. The prevalence of positive sentiments reflects a strong appreciation and enthusiasm among audiences for Indonesian gastronomic experiences, indicating a favorable perception and reception towards the nation's culinary richness and cultural heritage. This abundance of positive feedback underscores the significance of gastronomy as a driving force in promoting Indonesia's culinary tourism sector and enhancing its global appeal as a destination renowned for its diverse and flavorful cuisine. Consequently, the widespread positivity towards Indonesian gastronomy content highlights its pivotal role in fostering cultural appreciation, culinary exploration, and tourism development within the country.

Therefore, the findings of this study recommend the enhancement of tourism and gastronomy content, alongside the support for food influencers to intensify their efforts in marketing the allure of Indonesian culinary and cultural experiences. By elevating the quality and diversity of tourism and gastronomy content, stakeholders capture the attention and interest of both domestic and international audiences, thereby promoting Indonesia as a premier culinary destination. Furthermore, by providing more significant support and resources to food influencers, such as training programs, collaborations with local communities, and access to promotional platforms, and effectively amplify their role as ambassadors of Indonesian cuisine and culture, ultimately contributing to the growth and sustainability of the country's culinary tourism industry.

4. CONCLUSION

In conclusion, this research has effectively explored public sentiment toward tourism and gastronomy content by employing sentiment classification methodologies. Through applying sentiment analysis techniques, including Vader and TextBlob, distinct patterns of sentiment distribution were observed within the dataset. The findings revealed a predominant prevalence of positive sentiments (72.19%), followed by neutral (23.33%) and negative sentiments (4.48%). These results provide valuable insights into the overall sentiment dynamics surrounding tourism and gastronomy content, highlighting the predominantly positive reception among users. Such findings underscore the importance of sentiment analysis in understanding user perceptions and attitudes, offering valuable implications for content creators, marketers, and policymakers in these domains. Moving forward, future research endeavors could delve deeper into the underlying factors influencing sentiment expressions and explore strategies to leverage positive sentiments to promote and enhance tourism and gastronomy experiences.

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REFERENCES

[1] J. Kokkranikal and E. Carabelli, “Gastronomy tourism experiences: the cooking classes of Cinque Terre,” *Tour. Recreat. Res.*, vol. 49, no. 1, pp. 161–172, 2024, doi: 10.1080/02508281.2021.1975213.
[2] K. P. Sio, B. Fraser, and L. Fredline, “A Contemporary systematic literature review of gastronomy tourism and destination image,” *Tour. Recreat. Res.*, 2021, doi: 10.1080/02508281.2021.1997491.
[3] R. Y. M. Yong, B. L. Chua, H. Han, and B. Kim, “Taste your way across the globe: a systematic review of gastronomy tourism literature (2000-2021),” *J. Travel Tour. Mark.*, vol. 39, no. 7–9, pp. 623–650, 2022, doi: 10.1080/10548408.2023.2184445.
[4] F. Badu-Baiden, A. Correia, and S. Kim, “How do tourists’ memorable local gastronomy experiences and their personal gastronomic traits influence destination loyalty? A fuzzy set approach,” *J. Travel Tour. Mark.*, vol. 39, no. 5, pp. 501–515, 2022, doi: 10.1080/10548408.2022.2148041.
[5] Y. Jeaheng *et al.*, “Influence of Thai Street Food Quality, Price, and Involvement on Traveler Behavioral Intention: Exploring Cultural Difference (Eastern versus Western),” *Psychol. Res. Behav. Manag.*, vol. 16, pp. 223–240, 2023, doi: 10.2147/PRBM.S371806.
[6] S. Kaur and M. Kaur, “Image of Local Cuisine in Emerging Gastronomic Destinations: Scale Review, Development, and Validation,” *Int. J. Hosp. Tour. Adm.*, vol. 25, no. 1, pp. 153–201, 2024, doi: 10.1080/15256480.2022.2092247.
[7] P. Björk, N. Prebensen, J. Räikkönen, and J. Sundbo, “20 years of Nordic tourism experience research: a review and future research agenda,” *Scand. J. Hosp. Tour.*, vol. 21, no. 1, pp. 26–36, 2021, doi: 10.1080/15022250.2020.1857302.
[8] H. Ekizler, M. Öksüz, B. Durmuş, and Z. Dilistan Shipman, “Antecedents of tourist food consumption: food choice motives of foreign tourists in Turkey,” *Anatolia*, vol. 34, no. 4, pp. 494–508, 2023, doi: 10.1080/13032917.2022.2070856.
[9] E. Marine-Roig, M. P. Lin, and N. Llonch-Molina, “Cooking Classes as Destination Image Contribution: A Serious Leisure Perspective,” *Leis. Sci.*, vol. 0, no. 0, pp. 1–22, 2023, doi: 10.1080/01490400.2023.2253806.
[10] A. Wondirad and G. Verheye, “Does gastronomy determine visitors’ holiday destination choice? Empirical evidence based on a mixed-method research approach,” *Cogent Food Agric.*, vol. 9, no. 2, 2023, doi: 10.1080/23311932.2023.2266195.
[11] S. Moral-Cuadra, M. Solano-Sánchez, A. Menor-Campos, and T. López-Guzmán, “Discovering gastronomic tourists’ profiles through artificial neural networks: analysis, opinions and attitudes,” *Tour. Recreat. Res.*, vol. 47, no. 3, pp. 347–358,

Building of Informatics, Technology and Science (BITS)
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DOI 10.47065/bits.v5i4.5033

2022, doi: 10.1080/02508281.2021.2002630.
[12] J. Lima, J. Serra, M. D. R. Borges, and N. Marujo, "Is gastronomy important for UNESCO world heritage sites' tourists? A case study from Portugal," *Anatolia*, vol. 00, no. 00, pp. 1–13, 2023, doi: 10.1080/13032917.2023.2191268.
[13] A. Giampiccoli, E. M. Mnguni, A. Dłużewska, and O. Mtapuri, "Potatoes: Food tourism and beyond," *Cogent Soc. Sci.*, vol. 9, no. 1, 2023, doi: 10.1080/23311886.2023.2172789.
[14] U. Kattiyapornpong, M. Ditta-Apichai, and C. Chuntamara, "Exploring gastronomic tourism experiences through online platforms: evidence from Thai local communities," *Tour. Recreat. Res.*, vol. 47, no. 3, pp. 241–257, 2022, doi: 10.1080/02508281.2021.1963920.
[15] Anubha, S. Hussain, M. R. Gavinolla, V. G. B. Gowreesunkar, and S. K. Swain, "Retrospective overview on global food tourism and related research: a bibliometric analysis," *J. Foodserv. Bus. Res.*, vol. 00, no. 00, pp. 1–30, 2023, doi: 10.1080/15378020.2023.2228672.
[16] M. Demir and A. Dalgıç, "Examining gastronomy festivals as the attractiveness factor for tourism destinations: The case of Turkey," *J. Conv. Event Tour.*, vol. 23, no. 5, pp. 412–434, 2022, doi: 10.1080/15470148.2022.2089797.
[17] Dhun and H. K. Dangi, "Influencer Marketing: Role of Influencer Credibility and Congruence on Brand Attitude and eWOM," *J. Internet Commer.*, vol. 22, no. S1, pp. S28–S72, 2023, doi: 10.1080/15332861.2022.2125220.
[18] L. Janssen, A. P. Schouten, and E. A. J. Croes, "Influencer advertising on Instagram: product-influencer fit and number of followers affect advertising outcomes and influencer evaluations via credibility and identification," *Int. J. Advert.*, vol. 41, no. 1, pp. 101–127, 2022, doi: 10.1080/02650487.2021.1994205.
[19] N. H. Nazlan, H. Zhang, J. Sun, and W. Chang, "Navigating the online reputation maze: impact of review availability and heuristic cues on restaurant influencer marketing effectiveness," *J. Hosp. Mark. Manag.*, vol. 33, no. 3, pp. 288–307, 2023, doi: 10.1080/19368623.2023.2246471.
[20] J. Nilsson, R. Murto, and H. Kjellberg, "Influencer marketing and the 'gifted' product: framing practices and market shaping," *J. Mark. Manag.*, vol. 39, no. 11–12, pp. 982–1011, 2023, doi: 10.1080/0267257X.2023.2253450.
[21] C. Miguel, C. Clare, C. J. Ashworth, and D. Hoang, "Self-branding and content creation strategies on Instagram: A case study of foodie influencers," *Inf. Commun. Soc.*, pp. 1–21, 2023, doi: 10.1080/1369118X.2023.2246524.
[22] M. Sharma and Y. Peng, "How Visual Aesthetics and Calorie Density Predict Food Image Popularity on Instagram: A Computer Vision Analysis," *Health Commun.*, vol. 39, no. 3, pp. 577–591, 2024, doi: 10.1080/10410236.2023.2175635.
[23] E. Polat, F. Çelik, B. Ibrahim, and D. Gursoy, "Past , present , and future scene of influencer marketing in hospitality and tourism management," *J. Travel Tour. Mark.*, vol. 41, no. 3, pp. 322–343, 2024, doi: 10.1080/10548408.2024.2317741.
[24] E. Gommeh, K. Schroën, and T. Metze, "Processed food dream or nightmare? Influential online sentiment coalitions," *NJAS Impact Agric. Life Sci.*, vol. 94, no. 1, pp. 80–111, 2022, doi: 10.1080/27685241.2022.2108731.
[25] C. Barnes, "Precarious digital mothering: creativity, entrepreneurship and hidden labor within digital foodscapes," *Food, Cult. Soc.*, vol. 26, no. 5, pp. 1154–1173, 2023, doi: 10.1080/15528014.2022.2100972.
[26] Y. A. Singgalen, "Implementasi Metode CRISP-DM dalam Analisis Model Pendukung Keputusan Simple Additive Weighting dan Pengembangan Basis Data Riwayat Pembelian Layanan Akomodasi Hotel," *J. Sist. Komput. dan Inform.*, vol. 5, no. 2, pp. 308–317, 2023, doi: 10.30865/json.v5i2.7153.
[27] Y. A. Singgalen, "Penerapan Metode CRISP-DM dalam Klasifikasi Data Ulasan Pengunjung Destinasi Danau Toba Menggunakan Algoritma Naïve Bayes Classifier (NBC) dan Decision Tree (DT)," *J. Media Inform. Budidarma*, vol. 7, no. 3, pp. 1551–1562, 2023, doi: 10.30865/mib.v7i3.6461.
[28] Y. A. Singgalen, "Penerapan CRISP-DM dalam Klasifikasi Sentimen dan Analisis Perilaku Pembelian Layanan Akomodasi Hotel Berbasis Algoritma Decision Tree (DT)," *J. Sist. Komput. dan Inform.*, vol. 5, no. 2, pp. 237–248, 2023, doi: 10.30865/json.v5i2.7081.
[29] Y. A. Singgalen, "Penerapan Metode CRISP-DM untuk Optimalisasi Strategi Pemasaran STP (Segmenting , Targeting , Positioning) Layanan Akomodasi Hotel , Homestay , dan Resort," *J. Media Inform. Budidarma*, vol. 7, no. 4, pp. 1980–1993, 2023, doi: 10.30865/mib.v7i4.6896.
[30] S. A. Kareem and P. Venugopal, "Examining the relationship between gastronomic experience, revisit intention, destination image and destination brand love: a moderating role of cewebrity reviews," *Leis. Loisir*, vol. 00, no. 00, pp. 1–27, 2023, doi: 10.1080/14927713.2023.2211582.
[31] Ö. Davras and İ. Özperçin, "The relationships of motivation, service quality, and behavioral intentions for gastronomy festival: the mediating role of destination image," *J. Policy Res. Tour. Leis. Events*, vol. 15, no. 4, pp. 451–464, 2023, doi: 10.1080/19407963.2021.1968881.
[32] S. N. Shetu, "Application of Theory of Planned Behavior (TPB) on fast-food consumption preferences among generation Z in Dhaka City, Bangladesh: an empirical study," *J. Foodserv. Bus. Res.*, vol. 00, no. 00, pp. 1–36, 2022, doi: 10.1080/15378020.2022.2086420.