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A Study on Perception of Audience About Digital Promotion of Instant Noodles: Application of Sentiment Analysis

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Abstract
The purpose of this study is to examine how the significance of digital promotions on social media influences audience perception. It explores how aligning advertisements with audience preferences fosters positive perceptions, while irrelevant content activates negative responses. Focusing on instant noodle brands, the research analyses sentiment to uncover the relationship between audience perception and sentiment. Using both exploratory and conclusive research designs, the study analyses 1,200 YouTube comments on advertisements for Maggi, Ching's, and Knorr, with 349 comments selected for sentiment analysis via the BERT model. Chi-square and ANOVA tests reveal significant differences in sentiment, with Ching's receiving the highest sentiment score and Maggi the lowest. The findings emphasize the need for marketers to create relevant and value-driven digital promotions to enhance brand perception. This study offers original insights into how social media feedback and sentiment analysis can refine digital marketing strategies, benefiting brands in aligning with audience preferences.

Keywords: Digital Promotion, Audience Preference, Audience Perception, Natural Language Processing and Sentiment Analysis

1.0 Introduction
In recent years, the marketing environment has shifted considerably, with digital platforms becoming central to how brands communicate with their audiences. Promotion is no longer confined to traditional media, instead, companies increasingly use social media networks, search engines and online communication channels to reach and influence consumers. According to Dasić et al. (2023), the perception of digital promotion is shaped by how individuals interpret and emotionally respond to marketing content circulating through these digital channels. These platforms allow businesses to present their products in more interactive and visually engaging ways, inviting audiences to not only receive but also react and contribute to the promotional messages.
Dwivedi et al. (2021) pointed out that digital promotions are more effective when the content matches the interests, life style and behaviour patterns of the audience. When promotional messages appear relatable and meaningful, they tend to foster stronger emotional connections with the brand. On the other hand, Barac (2023) emphasized that promotions viewed as irrelevant and excessive can cause irritation and may

even lead to negative attitude toward the brand. Hence, designing promotional content that is attention-worthy yet respectful of user boundaries is vital. This balance between engagement and discretion often determines how audiences ultimately view a brand and its communications.

Understanding audience perception is therefore not just beneficial – it is essential. How consumers interpret promotional messages can influence their buying decisions, their level of satisfaction, and their loyalty over time. Businesses rely on these insights to refine product features, communication styles, and overall marketing strategies. Devlin et al. (2019) noted that a significant portion of feedback today is gathered from online interactions, reviews, and discussions across platforms. However, this feedback is mostly unstructured text, manually reviewing it is neither practical nor efficient. For this reason, Natural Language Processing (NLP) has become a necessary tool to systematically analyse consumer opinions and detect recurring patterns in attitudes and emotional expressions.

The rise of social media has expanded both the scale and complexity of audience participation. Millions of people share opinions online every day, making these platforms a rich source of consumer insights. Drus et al. (2019) explained that sentiment analysis, widely used NLP technique, helps classify the emotional tone of text by identifying whether an expressed opinion is positive, negative or neutral. Although language styles, cultural influences, and emotional nuances present certain analytical challenges, the growth of machine learning and artificial intelligence has significantly enhanced the accuracy of sentiment interpretation. Wankhade et al. (2022) added that sentiment analysis continues to gain importance across several professional fields because it allows organizations to understand attitudes and responses on a large.

The expansion of digital promotional strategies has also influenced how consumers think about brands and products. Dwivedi et al. (2021) observed that interactive digital platforms help brands engage with audience more directly, encouraging dialogue rather than one -way communication. This responsiveness can improve brand favourability and strengthen trust. Yet, as Bryla et al. (2022) Pointed out that, when digital promotion is poorly planned Being too repetitive or lacking relevance, it can lead to disengagement and negative perception Therefore, promotional efforts must be carefully curated so that they connect with audiences while maintaining relevance and authenticity.

Suhaimin et al. (2023) described sentiment analysis as a method used to capture the underlying emotional intent of a piece of text, enabling researchers to understand how people actually feel about their particular message or topic. While in sentiment analysis provides valuable insights, it also requires attention to data ethics, contextual interpretation, and cultural sensitivity due to the personal nature of online communication.

In this context, examining the digital promotion of instant noodles is particularly meaningful. Instant noodles are widely consumed across age groups and social backgrounds, making them culturally familiar and emotionally relatable. They frequently appear in everyday discussions, recipe sharing, review videos and influencer demonstrations online. Studying how audiences react to digital promotions of instant models helps reveal how emotional association, daily habits and digital engagement come together to shape consumer perception. By applying sentiment analysis, this study aims to uncover how audiences express their experiences and feelings about instant noodles in digital environments, providing insights that can help brands strengthen communication strategies and consumer relationships.

1.1 Objective

- To find out the difference in sentiment score considering the three advertisements of three different brands.

- To find out the chance of association of audience perception with sentiment score concerning three brands of instant noodles.

2.0 Review of Literature

The rapid expansion of digital communication technologies has fundamentally reshaped how audiences interact with brands, evaluate products and make purchasing decisions, particularly within the Fast-Moving Consumer Goods (FMCG) sector. Digital platforms such as social media networks, online retail sites and company managed virtual communities have enabled consumers to access product information instantly while allowing businesses to engage users in more personalized and interactive ways. Scholars consistently highlight that modern marketing strategies must account not only for the functional delivery of promotional content but also for how audiences perceive, interpret, and emotionally respond to these messages in an online environment. Huseynzade (2023) noted that marketing communications has a direct influence on consumer purchase behaviour and the selection of appropriate promotional tools must be carefully aligned with the context of specific product categories. Rai (2023) further emphasized that widespread technological literacy, coupled with the continuous use of smartphones, tablets and laptops, has strengthened consumer confidence in engaging with digital promotions, making personalization an increasingly critical driver of purchase intention. Maheshwari (2023) supports this perspective, arguing that artificial intelligence-powered practices such as personalized recommendations, predictive analytics, and targeted advertisements are transforming the FMCG landscape by creating opportunities for businesses to refine audience engagement and foster deeper brand loyalty. The literature suggests that consumers respond positively when digital promotions provide relevant, relatable, and value driven content. However, when these promotions are excessively poorly timed or perceived as intrusive, they can trigger adverse reactions and reduce brand favourability, as noted by Barack (2023). Therefore, digital promotion strategies must balance brand messaging with sensitivity to consumer expectations and preferences.

A recurring theme across studies relates to the vital role of user-generated content (UGC) and the interactive nature of online spaces in shaping audience perception. Social media platforms provide consumers with avenues to express personal opinions, share product experiences, and influence the perspectives of others within their networks. Grljević et al. (2018) highlighted that such freely expressed feedback constitutes a valuable resource for organizations, enabling them to recognize shifts in audience expectations and adapt offerings accordingly Nandi et al. (2022) further explained that the always-active environment of social media requires brands to consistently monitor and interpret audience sentiment to maintain engagement. Rosokhata (2020) also noted that consumer conversations on digital platforms increasingly influence purchase decisions, with users comparing brands, evaluating competing products, and depending on social feedback to validate their choices. This dynamic creates a digital ecosystem in which brands must remain attentive to the tone, themes, and emotional signals embedded in online discussions. Wang et al. (2022) demonstrated that active engagement on social media can boost customer loyalty in service-driven contexts by fostering an environment of trust and responsiveness. Sharma et al. (2023) emphasized that businesses must pay attention to the influence of service quality and social media-based interactions on continued customer use, indicating that digital platforms are not just communication channels but evolving spaces of relationship building. Singh (2021) also highlighted the influence of psychological differences on consumer response to FMCG advertising, suggesting that levels of self-monitoring influence how individuals interpret promotional content and act upon it. From a platform usability perspective Singh et al. (2019) stated that the quality of information and ease of navigation strongly predict continued audience use, implying that digital promotion must align both with emotional resonance and functional accessibility. Meanwhile Talwar et al. (2021) noted that dissatisfaction with platform experience can lead users to switch to alternatives, further reinforcing the need for brands to maintain relevant and engaging interactions. Vohra (2023) added that the rise of digital literacy encourages audiences to research brands before purchasing, placing greater emphasis on positive social media communication. Collectively, these studies illustrate that audience perceptions are shaped not simply by promotional messages but by an ongoing dialog between consumers and companies within participatory digital environments.

Alongside growing recognition of role of user interaction, there has been substantial academic interest in sentiment analysis as a methodological tool for understanding online audience perceptions. As consumers increasingly communicate in open digital spaces, organizations require efficient methods to interpret vast amount of unstructured text. Drus (2019) examined sentiment analysis in social media contexts, noting the use of both lexicon based and machine learning approaches such as SentiWordNet, TF-IDF, Naïve Bayes and Support Vector Machines. These tools enable researchers to classify opinions and detect emotional tones, although results vary depending on linguistic nuance and platform communication style. Kaur et al. (2024) explained that sentiment analysis, supported by text mining and analytical models, provides critical insights into consumer preferences and helps businesses understand market trends in competitive environments. Ahmed et al. (2023) specifically explored how sentiment polarity can shift within social conversations, showing that negative perceptions may be moderated when businesses respond appropriately - a finding that highlights the importance of interaction style in consumer service exchanges. Capuano et al. (2021) introduced Hierarchical Attention Networks to classify sentiment in multilingual customer requests, demonstrating how advanced model architectures can address linguistic diversity. Meanwhile Polat (2022) used Aspect-Based Sentiment Analysis (ABSA) in dining contexts, to identify which restaurant attributes such as food quality, ambiance, or service drive satisfaction. Puschmann (2018) traced the evolution of sentiment analysis across computational, psychological, and social science domains arguing that while sentiment analysis provides faster insights than human evaluation, public misunderstanding of the technology remains common. Complimenting this Rambocas (2018) acknowledged both the potential and the limitations of sentiment analysis in marketing, suggesting improvements could be achieved by integrating machine learning with emerging techniques such as image processing. These perspectives collectively demonstrate that while sentiment analysis is a powerful tool for interpreting audience perceptions, its effectiveness depends on the sophistication of the models used, the contextual understanding of human emotion, and the ability to adapt analytical techniques to platform-specific communication patterns.

3.0 Research Methodology

This study follows a mixed methodological approach integrating both exploratory and conclusive research designs to understand how digital promotional activities for instant noodles influence audience sentiment. The exploratory phase enabled an initial understanding of the patterns and tones of audience responses, while the conclusive phase allowed for structured statistical evaluation of sentiment differences across selected advertisements. Three popular instant noodle brands – Maggi, Chings, and Knorr were chosen for analysis due to their wide consumer research and active presence on digital platforms. Each of these brands has been consistently relying on native-driven promotional content specially on YouTube, where audience engagement occurs in the form of comments, likes, shares and viewing duration. The advertisements selected for this research featured narratives centered on emotional household themes, particularly mother child bonding. While Chings and Knorr's promotions additionally incorporated celebrity appearances to shape aspirational appeal.

The data required for the study was collected directly from the comments section of Youtube, ensuring that the feedback analysed was organic, spontaneous and reflective of genuine audience perception. Power Automate was employed to facilitate the extraction and organization of this data, allowing for efficient handling of the large volume of comments without manual intervention. In total, 1200 comments were gathered across the advertisements of the three brands. From this data set, 349 comments were randomly selected for detailed analysis, ensuring that the sample retained diversity in sentiment expression while still remaining manageable for close examination. The analytical phase was centered on the use of the bidirectional encoder representation from transfer transformers (BERT) model. As a pre-trained natural language processing model, BERT reads text bidirectionally, enabling it to interpret contextual meaning and subtle linguistic nuances better than conventional sentiment analysis techniques, which often rely on predefined dictionaries or simple word weightings. The model was fine-tuned on the extracted comments set to generate sentiment scores for each statement.

To facilitate statistical comparison, the sentiment identified by the BERT model was transformed into five standardized categories. Very Poor, Poor, Average, Good and Very Good. These sentiment classes allowed the analysis to move beyond subjective interpretation, making the findings more structured, quantifiable, and suited for inferential testing. Python served as the primary programming environment throughout the sentiment scoring process, due to its extensive library support and compatibility with machine learning frameworks. Once the sentiment categories were finalized the data moved into the conclusive phase of the research, where statistical tests were conducted to determine whether significant differences existed in audience reactions across the three advertisements. A One-Way ANOVA was used to test differences in sentiment means and before applying it, Levene's test was conducted to check for homogeneity of variance. In instances where the Levene's test indicated violation of homogeneity, robust alternatives such as Welch and Brown-Forsythe ANOVA were applied to ensure reliability of results.

Additionally, a Chi-Square test of association was employed to examine whether there was a statistically significant relationship between the type of advertisement and the sentiment categories assigned to audience comments. The two variables entered into this test were: (1) the three advertisement groups representing Maggi, Ching's and Knorr and (2) the five sentiment categories. The null hypothesis stated that no association existed between the sentiment category and advertisement type. Rejection of this hypothesis indicated that audience sentiment varied meaningfully across the brand's promotional content. To understand the strength of association, a contingency coefficient was also calculated.

The selection of Maggi, Chings and Knorr served not only practical relevance, giving their prominence in the instant noodle market, but also analytical value due to differences in their communication strategies. While Maggi focuses heavily on emotional relatability, Chings and Knorr emphasize aspirational and celebrity-centered appeal. The use of audience comments combined with advanced NLP and statistical rigor provided a nuanced perspective on how these divergent promotional styles influence public perception offering insights beneficial for shaping future digital marketing strategies.

4.0 Analysis and Discussions

Digital advertising refers to the promotion of products or services through online channels, leveraging the

internet and digital platforms to deliver marketing messages to audiences. This form of advertising encompasses various formats, including display ads that appear on websites, apps, or social media platforms; search engine ads like Google Ads that are visible on search engine results pages; and social media ads promoted on platforms such as Facebook, Instagram, etc. Additionally, video ads are featured before, during, or after content on platforms like YouTube, while native ads seamlessly blend with platform content, such as sponsored articles or posts. Email marketing involves sending promotional messages directly to audiences as well as consumers, and influencer marketing collaborates with influencers to promote products or services through their digital channels. Digital advertising is data-driven, enabling businesses to target specific audiences, monitor performance, and adjust campaigns in real-time.
The three different brands of instant noodles used for the study are Maggi, Ching's and Knorr. The advertisement of Maggi showed a mother and child affection where the mother brings Maggi as the child feels hungry and that helps her to connect through her various memories related to various places and persons. Ching's on the other hand also showed mother and child affection but here the product is being introduced by a celebrity who is informing the mother about the product and that it can be used when the child feels hungry. Knorr also tapped the mother and child affection to convey the product information to the audience using a celebrity where the mother introduces the product to her child and her child's friends when they are chit chatting at her place and feels hungry.
Against these advertisements 349 comments have been collected from You Tube which has been converted in sentiment score in 1to5 point scale. The frequency distribution considering the advertisement of three brands on one hand and on the other the sentiment score is presented in the following table (Table No.1)

Table 1: Frequency Distribution

SENTIMENT	MAGGI	CHING'S	KNORR
1	37	17	37
2	10	3	5
3	18	7	19
4	8	21	14
5	35	73	45

From Table No.1 it can be stated that a Maggi advertisement has got highest frequency against sentiment score 1 whereas for both Ching's and Knorr the highest frequency corresponds to sentiment score 5. Even in comparing three advertisements based on sentiment score 5, it is found that the highest frequency is there for Ching's advertisement. In order to find out the statistical difference in the scores given by respondents across three advertisements of three brands, One-Way ANOVA has been conducted. Before applying ANOVA, the Levene's test is conducted to test the homogeneity of data. In the following table (Table No.2) Levene's Test has been conducted.

Table 2: Test of Homogeneity of Variances

Rating			
Levene Statistic	df1	df2	Sig.
3.111822049	2	314	0.045896

Levene's Test shows that *p* - value is less than .05. Therefore, Null Hypothesis is rejected. So, error variance is not equal, which denies the homogeneity of the data. There the ANOVA has become robust ANOVA, which cannot be considered for analysis. Instead, the Welch and Brown -Forsythe ANOVA has been applied to test the Null Hypothesis that the average mean sentiment score are equivalent for all three advertisements of three brands. The result of Welch and Brown- Forsythe ANOVA is in Table No.3

Table 3: Robust Tests of Equality of Means

Rating				
	Statistic	df1	df2	Sig.
Welch	6.231	2	205.061	.002
Brown-Forsythe	5.912	2	310.769	.003

As per the Table 3. It can be stated that Null Hypothesis is rejected as the *p* - value is less than .05. So, the mean sentiment score varies across the different advertisement of three different brands.

Figure 1: Mean of Rating

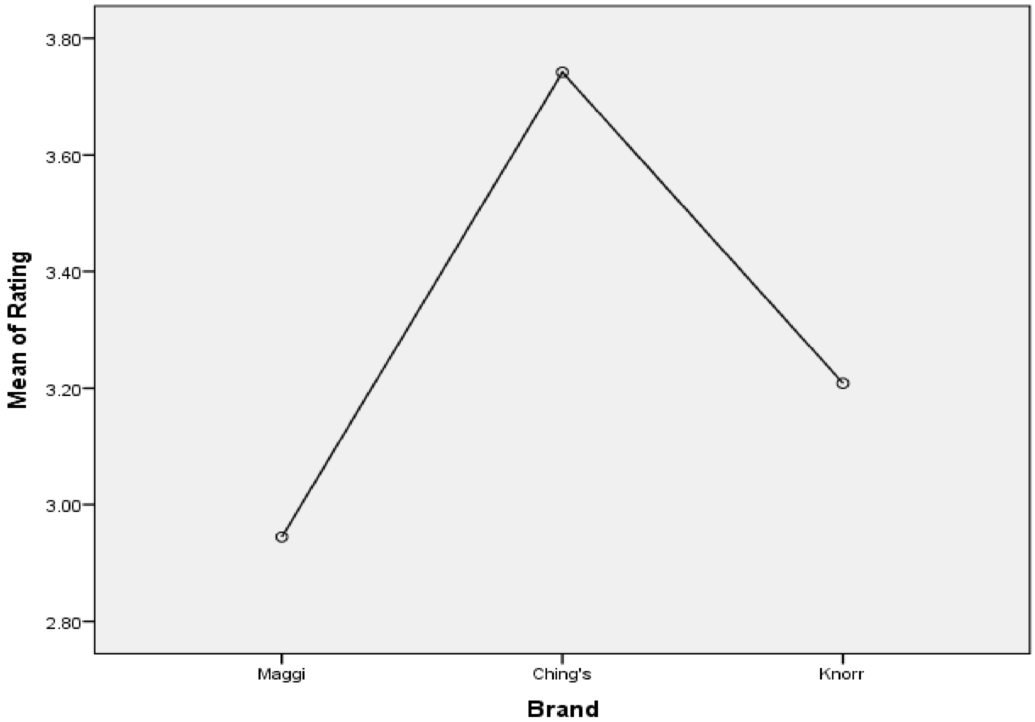

Figure 1. shows the highest sentiment score corresponds to the advertisement of Ching's that indicates more sentimental touch or emotional attachment have been found amongst the target audience of Ching's advertisement. However, the advertisement of Maggi shows the lowest sentiment score and advertisement of Knorr shows moderate sentiment score.

Another Hypothesis testing has been performed to measure the association between the promotional activities of three brands and sentiment scores of the comments of target audience regarding different promotional advertisements. The result of the Chi-square test is presented in Table No.4 below:

Table 4: Chi-Square Tests			
	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	23.567[a]	8	.003
Likelihood Ratio	23.434	8	.003
Number of Valid Cases	317		

As per the result of Table 4, it is found that Null Hypothesis (no significant association is there between the ratings based on sentiment score and the digital advertisements of three instant noodle brands) is rejected as *p* - value is less than .05. Therefore, it can be stated that there is significant association between the rating based on sentiment scores and the advertisements of three brands. In order to know how much association is there between the rating based on sentiment score and the digital advertisements of three brands, a contingency coefficient value has been determined. In Table 5 the value of contingency coefficient is presented.

Table 5: Symmetric Measures			
		Value	Approx. Sig.
Nominal by Nominal	Contingency Coefficient	0.263	0.003
Number of Valid Cases		317	

It is found from Table 5 that contingency coefficient value indicates moderate association between rating based on sentiment score and digital advertisements. Now it is important to find out the chance of association between different rating of sentiment scores and the digital advertisements of three brands. The chance of association in percentage is presented in Table 6.

Table 6: Chance of Association (%)		**Brand**			
		Maggi	Ching's	Knorr	**Total**
Rating	Very poor	34.3%	19.1%	30.8%	28.7%
	Poor	9.3%	3.4%	4.2%	5.7%
	Neither Poor nor Good	16.7%	7.9%	15.8%	13.9%
	Good	7.4%	23.6%	11.7%	13.6%
	Very Good	32.4%	46.1%	37.5%	38.2%
Total		100.0%	100.0%	100.0%	100.0%

Table 6 shows that the chance of association between the rating very poor and the advertisement of Maggi is highest that is 34.3%. Whereas, the chance of association between the rating very good and the advertisement of Ching's is highest that is 46.1%. In case of the advertisement of Knorr the chance of association is the highest for rating very good. It is important to explore the reason why the advertisement of Knorr and Ching's are more preferred by the target audience to the advertisement of Maggi.

The analysis of audience responses to digital promotional content for instant noodles reveals clear differences in how viewers emotionally connect with the advertisements of Maggi, Ching's and Knorr. Each advertisement employed a similar narrative of mother-child affection; however, the level of emotional resonance varied across brands. The frequency distribution of sentiment scores shows that the Maggi advertisement received the highest proportion of "very poor" responses, while both ching's and Knorr Show to the highest frequencies in the "very good" sentiment category. Among the three, Ching's advertisements achieved the strongest positive sentiment, indicating a deeper emotional appeal compared to the others.

The Levene's test result confirmed unequal variances in the data, leading to the application of Welch and Brown-Forsythe ANOVA, where the outcome demonstrated that the mean sentiment scores differ significantly across the three advertisements. This suggests that viewers did not respond uniformly, and each brand's promotional style influenced sentiment differently. The Chi-square test further supported this by showing a significant association between sentiment categories and advertisement type. The contingency coefficient indicated a moderate degree of association meaning the type of advertisement played a meaningful role in shaping viewer sentiment.

The higher positive response for Ching's and Knorr is linked to the presence of celebrity endorsements, which earlier studies highlights as influential in enhancing trust, appeal and purchase intention when executed strategically (Mythili et al., 2024; Vidoni, 2020; Darmawan et al., 2024). However, literature also cautions that celebrity influence can be negatively affected by controversies or overexposure (Vidoni, 2020; Zuhri et al., 2024). Thus, the findings suggest that while emotional storytelling is important, celebrity integration can substantially strengthen audience connection when managed thoughtfully.

5.0 Conclusion and Implications

The study set out to understand how audiences perceive digital advertising for three instant noodle brands by examining viewer comments and their sentiment ratings. The results demonstrate that emotional tone and advertising strategy strongly influence how audiences interpret and respond to promotional content. While all three advertisements relied on mother-child affection as a core narrative, the responses varied notably across brands. Ching's generated the highest positive sentiment, followed by Knorr, whereas Maggi's advertisement received comparatively low sentiment scores. This difference can be traced to the presence of celebrity figures in Ching's and Knorr's campaigns, which appeared to strengthen reliability, emotional appeal and perceived credibility. Earlier research supports this pattern, suggesting that celebrity endorsers can positively shape audience attitudes when they are seen as trustworthy, appealing and well aligned with the brand (Mythili et al.,2024; Vidnoni,2020; Darmawan et al.,2024). However, the literature also emphasizes the need to approach such endorsements carefully due to risks like negative publicity or message dilution (Vindoni, 2020; Zuhri et al., 2024).

The implications of this finding are significant for digital marketing strategy. Brands aiming to build strong emotional connections must pay close attention to narrative tone, message authenticity and the symbolic associations created through endorsers. Further, this study suggests that sentiment analysis provides a valuable window into real-time audience feedback, helping marketers refine promotional decisions. Future research could extend this work by examining whether higher positive sentiment collates with actual purchase behaviour and by exploring how specific creative elements within digital advertisements contribute to emotional engagement and long-term brand preference.

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