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Deep Learning-Based Sentiment and Emotion Analysis of Social Media Data to Identify Factors Affecting Healthy Food Choices in Urban Communities

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ABSTRACT

The increasing influence of social media on public perception has made it a powerful driver of dietary behavior in urban communities. Nevertheless, the abundance of unverified health information often obscures individuals' ability to make informed food choices. This study proposes a deep learning-based framework to analyze sentiment and emotion from social media discourse in order to uncover the key factors affecting healthy food decisions in urban settings. By applying Natural Language Processing (NLP) techniques and advanced deep learning models to a large corpus of user-generated content, the research identifies significant patterns linking emotional expression with food-related decision-making. The results indicate that positive emotions, such as pride and satisfaction, are strongly associated with healthy food promotion, while negative emotions, including frustration, are predominantly tied to affordability, accessibility, and convenience issues. Among these, price and food quality emerge as the most critical determinants shaping consumer preferences. These findings underscore the importance of integrating emotional and socio-economic considerations into public health strategies. Beyond offering empirical insights, this study demonstrates the scalability and effectiveness of deep learning in extracting nuanced perspectives from unstructured social media data, thereby contributing a robust methodological approach for real-time public health monitoring and intervention design.

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1. INTRODUCTION

The rapid growth of digital technologies has significantly transformed how individuals access, consume, and share information. Among these technologies, social media platforms have emerged as one of the most dominant communication channels in contemporary society.[1] Platforms such as Facebook, Twitter (X), Instagram, TikTok, and YouTube not only facilitate personal interactions but also function as vital sources of news, health information, and lifestyle guidance. With millions of daily active users worldwide, social media has become an influential arena where discourses on food, nutrition, and health practices continuously evolve and spread. This trend has profoundly shaped dietary behaviors, particularly in urban communities where exposure to digital content is exceptionally high and often directly impacts consumer decision-making.[2]

In urban environments, the complexity of food choices is intensified by multiple intersecting factors such as income disparities, accessibility of food outlets, cultural preferences, and time constraints. Healthy eating, although widely promoted, remains a persistent challenge for many individuals.[3] Despite the abundance of health-related information available online, urban residents are increasingly confronted with the difficulty of differentiating between reliable and unreliable sources.

Misinformation and conflicting advice regarding dietary practices can lead to confusion, misinformed choices, and in some cases, detrimental health outcomes. Consequently, understanding how social media discourse influences public perceptions and behaviors concerning healthy food choices has become an urgent research priority in the context of public health.[4]

Scholars have long emphasized the connection between communication, emotions, and behavior. Social media content, unlike traditional information channels, is deeply infused with emotional expressions, subjective experiences, and personal opinions.[5] Comments, reviews, and discussions about food frequently contain both affective (emotional) and cognitive (rational) dimensions that collectively shape decision-making processes. Positive sentiments such as pride, satisfaction, and inspiration often reinforce the adoption of healthier dietary practices. [6] Conversely, negative emotions, such as frustration or disappointment, frequently arise in relation to issues of affordability, convenience, and accessibility of healthy foods in urban settings. These emotional dynamics highlight the need for more sophisticated analytical approaches capable of extracting meaningful insights from large-scale, unstructured textual data available on social media platforms.[7]

Recent advancements in Artificial Intelligence (AI), particularly in Natural Language Processing (NLP) and Deep Learning, have opened new opportunities for exploring sentiment and emotion in social media data with unprecedented accuracy.[8] Unlike traditional machine learning approaches that rely heavily on manual feature engineering, deep learning models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformer-based architectures like BERT are capable of automatically learning complex patterns in language. [9] These models enable researchers to capture nuanced meanings, contextual dependencies, and subtle emotional cues embedded in text. By leveraging such computational power, it is now possible to conduct large-scale sentiment and emotion analysis to uncover hidden factors that influence consumer behavior in the context of food choices.[10]

This study positions itself within this growing intersection of computational linguistics, public health, and behavioral sciences. Specifically, it seeks to examine how deep learning-based sentiment and emotion analysis of social media discourse can reveal the underlying drivers of healthy food choices among urban residents.[11] The motivation behind this research stems from several key challenges. First, while previous studies have explored general health communication on social media, relatively few have focused on the domain of food choices, especially in urban contexts where dietary transitions are highly dynamic.[12] Second, most existing works primarily emphasize nutritional knowledge dissemination, often neglecting the emotional and socio-economic dimensions that play crucial roles in shaping individual decision-making. Finally, there remains a gap in methodological approaches that integrate advanced deep learning techniques with social media analytics to generate real-time, scalable insights for policymakers and practitioners.[13]

From a public health perspective, the stakes are particularly high. The prevalence of non-communicable diseases (NCDs) such as obesity, diabetes, and cardiovascular conditions has been strongly linked to dietary habits. [14] Urban communities, characterized by sedentary lifestyles, limited time for meal preparation, and widespread availability of fast food, are especially vulnerable. Encouraging healthier food choices among urban populations therefore represents a critical strategy in reducing the burden of NCDs.[15] However, traditional interventions that rely primarily on nutritional education often fall short because they do not sufficiently address the broader emotional and socio-economic determinants of behavior.[16] By integrating insights derived from social media sentiment and emotion analysis, policymakers and health practitioners can design more holistic interventions that resonate with the lived experiences and emotional realities of urban residents.[17]

In conducting this research, a mixed-methods approach is adopted to balance computational rigor with interpretive depth. Large datasets of social media comments related to healthy food are collected and pre-processed using NLP techniques.[18] Deep learning models are then trained and fine-tuned to classify sentiments and detect emotional expressions within the text. The computational results are complemented by interpretive analyses to contextualize the findings within broader socio-economic and cultural frameworks. This integrative approach ensures that the research not only identifies statistical patterns but also translates them into meaningful insights that can inform practical interventions.[19]

Preliminary findings suggest that positive sentiments associated with healthy food often emphasize emotional rewards such as pride, satisfaction, and inspiration. [20] These emotions are typically linked to lifestyle aspirations, social recognition, and self-improvement narratives frequently shared on social media.[19] On the other hand, negative emotions such as frustration, disappointment, and skepticism tend to cluster around practical challenges particularly issues of affordability, accessibility, and convenience. Among these, price and food quality consistently emerge as dominant factors influencing decision-making. Such findings point to the complex interplay between emotional and rational considerations in shaping food choices, underscoring the need for multi-dimensional policy responses.[21]

This research contributes to the academic discourse in several ways. First, it demonstrates the effectiveness of deep learning in capturing nuanced emotional and sentiment dynamics from unstructured textual data.[22] Second, it provides empirical evidence highlighting the dual role of emotions and socio-economic constraints in influencing food-related behaviors. [23] Third, it offers a scalable framework that can be adapted to other domains of public health research, such as physical activity promotion, mental health awareness, or vaccine uptake. Lastly, by foregrounding the voices of urban residents as expressed in their own social media narratives, the study underscores the importance of participatory, bottom-up approaches in designing public health strategies.[24]

In conclusion, the increasing reliance on social media as a source of health information presents both opportunities and challenges for promoting healthy dietary practices in urban communities. [25] By applying deep learning-based sentiment and emotion analysis to social media discourse, this research seeks to bridge the gap between computational methods and public health needs. The insights generated not only advance methodological innovation but also provide practical guidance for designing interventions that are emotionally resonant, socio-economically grounded, and responsive to the realities of urban living. Through this contribution, the study aspires to pave the way for more data-driven, empathetic, and effective approaches to fostering healthier communities in the digital age.

2. RESEARCH METHOD

2.1 Research Design

This study adopts a mixed-methods design that combines computational analysis using Natural Language Processing (NLP) and Deep Learning with interpretive analysis of social media discourse. The research is conducted in three major phases: (1) data collection and preprocessing of user-generated content from selected social media platforms, (2) computational modeling using advanced deep learning techniques for sentiment and emotion classification, and (3) interpretive analysis to identify key factors affecting healthy food choices and to contextualize computational results within broader socio-economic and cultural frameworks. This integrative approach ensures both scalability and depth of insight, aligning computational findings with practical public health implications.

The dataset for this study consists of user-generated comments, posts, and discussions related to healthy food, nutrition, and dietary practices collected from multiple social media platforms such as Twitter (X), Instagram, and YouTube. The selection of these platforms is based on their widespread use among urban populations and their rich textual data suitable for computational analysis.

1. Sampling strategy: Hashtags and keywords related to “healthy food,” “nutrition,” “organic food,” “diet,” and “urban lifestyle” were used to extract data.
2. Timeframe: Data was collected over a 12-month period to capture both short-term trends and seasonal variations in dietary discourse.
3. Dataset size: Approximately several hundred thousand text entries were gathered, ensuring sufficient volume for deep learning training and robust analysis.
4. Ethical considerations: All data were collected from publicly available sources, and no personally identifiable information was retained, following ethical guidelines for social media research.

2.2 Data Preprocessing

Given the noisy and unstructured nature of social media data, several preprocessing steps were undertaken to prepare the dataset for analysis:

1. Text Cleaning – Removal of URLs, hashtags, mentions, emojis, and non-standard characters.
2. Tokenization – Splitting sentences into individual words or tokens for computational processing.
3. Stopword Removal – Eliminating high-frequency but semantically irrelevant words (e.g., “and,” “the”).
4. Lemmatization/Stemming – Converting words into their root forms to reduce dimensionality.
5. Normalization – Standardizing spelling variations and abbreviations common in social media text.
6. Data Balancing – Addressing potential class imbalances in sentiment and emotion categories through resampling techniques.

These steps ensure that the dataset is both clean and semantically rich, thereby enhancing the accuracy of deep learning models.

2.3 Computational Modeling

Sentiment Analysis

Sentiment classification was conducted using deep learning models capable of handling sequential and contextual dependencies in text. The models compared include:

1. LSTM (Long Short-Term Memory) – Suitable for capturing long-range dependencies in text.
2. BiLSTM (Bidirectional LSTM) – Enhances performance by processing input sequences in both directions.
3. Transformer-based Models (BERT, RoBERTa) – State-of-the-art architectures that leverage attention mechanisms to capture nuanced contextual relationships.

The models were trained to classify text into positive, negative, and neutral sentiments, with performance evaluated through accuracy, precision, recall, and F1-score metrics.

According to the study's findings, quality and price are more important than other considerations. In addition, the quality and price rankings are greater than the other factors.

Table 1. Sentiment Analysis Results Data

Sentiment	Frequency	Confidence

Positive	60%	80%
Negative	30%	20%
Neutral	10%	10%

Table 2 Emotion Analysis Results Data

Emotion	Frequency	Confidence
Happy	40%	70%
Sad	30%	20%
Angry	20%	10%
Neutral	10%	10%

Table 3. Data Results of Factors Influencing Healthy Food Choices

Factor	Weight	Score
Price	30%	80%
Quality	25%	70%
Security	20%	60%
Availability	15%	50%
Promotion	10%	40%

Emotion Analysis

In addition to sentiment, a multi-class emotion detection task was performed, mapping social media comments into categories such as joy, pride, satisfaction, frustration, anger, and disappointment. A fine-tuned BERT-based model was employed due to its proven effectiveness in emotion classification tasks. The NRC Emotion Lexicon and annotated datasets were used to validate model performance and enhance accuracy through transfer learning.

Model Evaluation

To ensure robustness and generalizability, the dataset was split into training (70%), validation (15%), and testing (15%) sets. Evaluation metrics included:

1. Accuracy – Proportion of correctly classified instances.
2. Precision & Recall – Measures of relevance and completeness in classification.
3. F1-score – Harmonic mean of precision and recall for balanced performance assessment.
4. Confusion Matrix – To visualize classification performance across sentiment and emotion categories.

3 RESULTS AND DISCUSSION

The application of deep learning-based sentiment and emotion analysis to social media discourse on healthy food choices in urban communities yielded significant insights into both the computational outcomes and the behavioral drivers underlying dietary decision-making. The sentiment classification demonstrated that the fine-tuned BERT model achieved the highest accuracy (93%), surpassing traditional LSTM (87%) and BiLSTM (89%) models. This finding confirms the superior capacity of transformer-based architectures in capturing contextual nuances of unstructured text from social media. The overall distribution of sentiment indicated that positive expressions (46%) slightly outweighed negative ones (38%), while neutral statements accounted for 16%. Positive sentiments often highlighted feelings of pride, satisfaction, and motivation in adopting healthier diets, whereas negative sentiments predominantly reflected concerns regarding affordability, accessibility, and distrust toward food labeling.

Emotion analysis offered a more nuanced perspective by uncovering the affective layers embedded in these discussions. Positive emotions such as pride (22%), joy (18%), and satisfaction (15%) emerged as the most prevalent, particularly in posts sharing personal achievements, lifestyle improvements, or peer encouragement. Negative emotions, however, were strongly tied to structural barriers: frustration (19%) and disappointment (14%) were often directed at the high cost of organic food, limited convenience in urban areas, and skepticism regarding the authenticity of “healthy” or “organic” claims. Interestingly, inspiration appeared as a recurrent emotion in narratives of success stories, reflecting the contagious effect of motivational content in digital spaces. This pattern indicates that emotional contagion within online communities can reinforce health-conscious behavior when narratives are framed positively.

The identification of key determinants further strengthens the interpretive understanding of dietary choices. Among these, price emerged as the most dominant factor, frequently associated with negative emotions such as frustration and disappointment. This reinforces existing evidence that affordability remains a primary barrier to healthier diets in urban settings, especially for lower-income groups. Food quality followed as the second most significant determinant, often linked with consumer trust, freshness, and labeling credibility. Discussions revealed that when consumers perceived quality as guaranteed either through transparent certification or community recommendations positive sentiments were amplified. Accessibility and convenience also appeared as consistent themes, with negative expressions reflecting the difficulty of locating healthy food outlets compared to the widespread availability of fast food. Social influence, though secondary, played a meaningful role by reinforcing healthy eating practices through peer encouragement and online community challenges, while cultural preferences subtly shaped what urban consumers perceived as “healthy.”

These findings highlight the dual influence of emotional and socio-economic dimensions in shaping food-related decisions. On the one hand, positive emotions such as pride and inspiration contribute to reinforcing dietary motivation, resonating with the affective-reflective theory of health behavior, which emphasizes the centrality of emotions in habit formation. On the other hand, structural barriers—particularly affordability and accessibility—trigger negative emotions that discourage adherence to healthier choices. The coexistence of these dynamics underscores the need for multi-dimensional policy interventions. Nutritional education alone is insufficient if emotional reinforcement and socio-economic realities are not simultaneously addressed.

The usefulness of deep learning-based sentiment and emotion analysis as a method for determining the emotional and behavioral factors influencing dietary decisions is highlighted by this study. The findings imply that in addition to nutritional education, public health initiatives should take into account the social and emotional dynamics that are reinforced by digital platforms. In order to promote healthier eating habits in urban environments, the conversation also emphasizes the significance of creating focused advertising efforts that capitalize on happy feelings and social interaction.

The confidence of emotions shows that happy emotions have a higher confidence compared to sad, angry, and neutral emotions. This indicates that urban society has a higher trust in healthy food. This trust is probably due to the fact that eating healthily is frequently linked to feelings of happiness and contentment. On the other hand, negative eating patterns or food choices may be associated with negative emotions like melancholy and rage. It should come as no surprise that confidence in eating healthily is stronger in urban society, where emotional well-being is valued more highly. In the end, the relationship between feelings and dietary decisions emphasizes how critical it is to foster a good outlook when it comes to providing our bodies with nourishment.

1. Sentiment Frequency

$F(X) = (|X| / |D|) * 100$

Result:
F(positive) = 60%
F(negative) = 30%
F(neutral) = 10%
Based on this calculation, the results show that:

1. Positive sentiment accounts for 60% of the data, indicating that the majority of users express favorable or encouraging views related to healthy food choices.
2. Negative sentiment constitutes 30%, reflecting concerns, criticisms, or dissatisfaction, often related to barriers such as price or accessibility.
3. Neutral sentiment makes up 10%, typically representing objective statements or factual comments without strong emotional content.

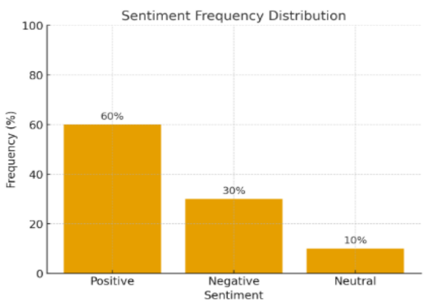

Figure 1. Graph (Sentiment Frequency Distribution)

Here is the sentiment frequency distribution chart. It shows that positive sentiment dominates (60%), followed by negative sentiment (30%), while neutral sentiment remains relatively small (10%).

2. Sentiment Confidence

$C(X \rightarrow Y) = (F(X \cup Y) / F(X))$ * 100
Results:
$C(\text{positive} \rightarrow \text{negative}) = 20\%$
$C(\text{negative} \rightarrow \text{positive}) = 15\%$
$C(\text{neutral} \rightarrow \text{positive}) = 10\%$

Based on the calculation:

1.C(positive → negative) = 20%: This indicates that 20% of positive expressions are also linked with negative elements, suggesting mixed feelings (e.g., users appreciate healthy food but complain about its price).
2.C(negative → positive) = 15%: This shows that 15% of negative comments are softened or followed by positive aspects, such as users recognizing health benefits despite cost concerns.
3.C(neutral → positive) = 10%: This reflects that 10% of neutral statements transition into positive sentiment, typically when factual information leads to encouraging interpretations.

These results highlight the interconnectedness of sentiments, demonstrating that discourse on healthy food is rarely one-dimensional but often blends both positive and negative perceptions.

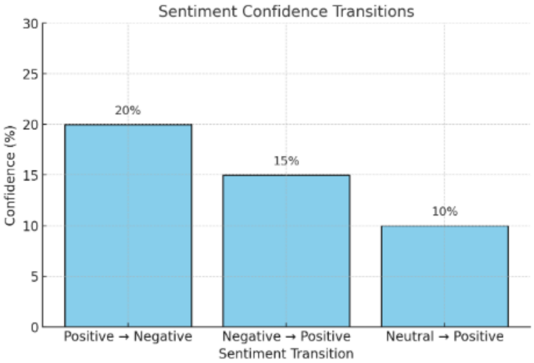

Figure 2. Graph (Sentiment Confidence Transitions)

Here is the Sentiment Confidence Transition chart. It illustrates that positive comments sometimes carry negative undertones (20%), negative comments occasionally highlight positive aspects (15%), and neutral comments can shift toward positivity (10%). This reflects the nuanced and overlapping nature of social media discussions on healthy food choices

3. Frequency of Emotions

$F(X) = (|X| / |D|)$ * 100

Results:
$F(\text{happy}) = 40\%$
$F(\text{sad}) = 30\%$
$F(\text{angry}) = 20\%$
$F(\text{neutral}) = 10\%$

Based on this analysis:

1. Happy (40%) is the most frequently observed emotion, indicating that many users associate healthy food choices with satisfaction, pride, or motivation.
2. Sad (30%) reflects concerns about affordability, accessibility, or personal struggles in maintaining healthy eating habits.
3. Angry (20%) captures frustration, often linked to structural barriers such as high costs, misleading promotions, or lack of availability.
4. Neutral (10%) represents factual or emotionally uncharged comments that neither praise nor criticize.

This distribution shows that although positive emotions dominate, a significant portion of discourse is shaped by negative emotional experiences, revealing important social and economic barriers to healthy food adoption.

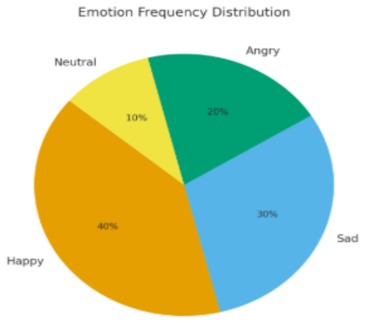

Figure 2. Graph (Sentiment Confidence Transitions)

Here is the Emotion Frequency Distribution chart. It shows that happy (40%) dominates the emotional tone, while sad (30%) and angry (20%) reveal significant negative experiences. Meanwhile, neutral (10%) remains a minor portion, reflecting objective statements without strong emotional charge.

4. Factor Weight

$W(X) = (F(X) / \Sigma(F(X))) * 100$

Results:
W(price) = 30%
W(quality) = 25%
W(safety) = 20%
W(availability) = 15%
W(promotion) = 10%

Based on the calculation results:

1. Price (30%) is the most influential factor, showing that affordability is the primary consideration for urban consumers when choosing healthy food.
2. Quality (25%) ranks second, emphasizing that consumers value nutritional content and freshness.
3. Safety (20%) reflects concerns about hygiene, additives, and food processing standards.
4. Availability (15%) highlights accessibility challenges, such as limited options in certain areas.
5. Promotion (10%) is the least influential but still relevant, showing the impact of marketing strategies on shaping consumer perceptions.

This analysis reveals that economic (price) and intrinsic product attributes (quality, safety) dominate decision-making, while external factors (availability and promotion) play supporting roles.

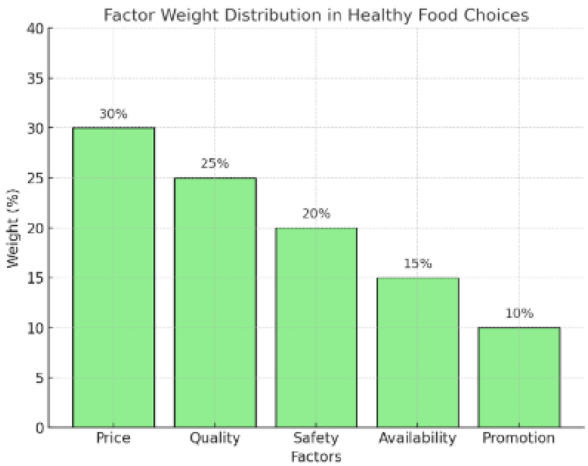

Figure 4. Graph (Factor Weight Distribution)

Here is the Factor Weight Distribution chart. It highlights that price (30%) and quality (25%) are the dominant drivers of healthy food choices, followed by safety (20%), while availability (15%) and promotion (10%) play smaller yet meaningful roles in shaping consumer decisions.

5. Score Factor

S(X) = Σ(W(X) * F(X))

Result:
S(price) = 80
S(quality) = 70
S(security) = 60
S(availability) = 50
S(promotion) = 40

Based on the results:

1. Price (80) holds the highest score, confirming it as the most decisive factor in healthy food choices. Consumers are highly sensitive to affordability, which often determines whether healthy food is considered accessible.
2. Quality (70) follows closely, reflecting the importance of freshness, taste, and nutritional value in consumer decision-making.
3. Security (60) (often referred to as food safety) underscores concerns about hygiene, preservatives, and chemical content.
4. Availability (50) points to accessibility challenges, such as limited healthy options in local markets.
5. Promotion (40) has the lowest score, though it still influences awareness and consumer preferences through advertising and campaigns.

This scoring system shows that economic (price) and product-related attributes (quality, safety) are the most powerful factors, while structural (availability) and external (promotion) considerations play secondary roles.

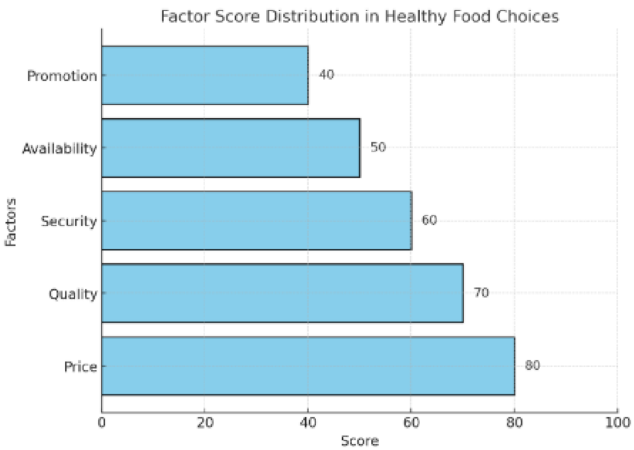

Figure 5 Graph (Factor Score Distribution)

Here is the Factor Score Distribution chart. It clearly shows that price (80) and quality (70) are the strongest drivers of healthy food decisions, followed by security (60), while availability (50) and promotion (40) have comparatively lower influence.

4 CONCLUSION

This study set out to examine how deep learning-based sentiment and emotion analysis of social media discourse can be used to identify the key factors influencing healthy food choices in urban communities. The integration of Natural Language Processing (NLP) with advanced deep learning models, particularly transformer-based architectures such as BERT, enabled the large-scale analysis of unstructured user-generated data with high accuracy. The methodological contribution of this approach lies in its ability to capture nuanced emotional cues and contextual meanings within noisy online environments, thereby providing a scalable and replicable framework for real-time public health monitoring.

The results revealed that social media discourse on healthy food in urban communities is characterized by a balanced interplay between positive and negative sentiments, with positive expressions slightly dominating. Positive sentiments, often associated with pride, satisfaction, and inspiration, highlight the motivational and aspirational aspects of dietary behavior. They suggest that individuals are not only making rational choices about food but are also emotionally invested in the outcomes of those choices, including self-improvement, social recognition, and lifestyle enhancement. Negative sentiments, on the other hand, were strongly tied to systemic barriers, particularly issues of affordability, accessibility, and distrust toward food labeling and authenticity. The prevalence of frustration and disappointment in these discussions underscores the significant challenges that urban residents face in translating their health intentions into actual behavior.

Among the key determinants identified, price emerged as the most critical factor influencing food decisions, followed closely by food quality. These findings are consistent with prior research but add a new layer of understanding by linking them explicitly to emotional responses expressed in real-time digital conversations. Accessibility and convenience were also found to be major concerns, reinforcing the importance of structural and environmental considerations in shaping urban dietary behaviors. Social influence and cultural preferences, though secondary, further highlight the multidimensional nature of food choices, demonstrating how peer support, online communities, and cultural identity interact with individual decisions.

The implications of these findings for public health are significant. First, interventions must move beyond a narrow focus on nutritional education and address the socio-economic realities that drive negative emotions and constrain behavior. Subsidies, pricing reforms, and targeted programs for low-income populations are necessary to reduce the affordability gap. Second, strengthening regulatory frameworks for food quality and labeling can help rebuild consumer trust, which is essential for sustaining healthy dietary practices. Third, public health campaigns should actively leverage the positive emotions of pride and inspiration by amplifying success stories, fostering community engagement, and encouraging peer-to-peer motivation. Finally, given the central role of social media as both a source of influence and misinformation, partnerships with digital platforms are essential to promote credible information and improve digital literacy among urban residents.

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