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# Can Artificial Intelligence Reliably Detect Risky Eating Narratives? A Comparative Analysis of YouTube Extreme Diet Videos

İrem BAŞÖREN*, Hilal AKSOY**, Abdullah Furkan KORKMAZ***, Zehra Margot ÇELİK****

**Abstract**

**Aim:** This descriptive study was conducted to identify characteristics that are related to binge eating in YouTube videos that have been shared with the keywords "extreme diet" and "diet challenge" and to compare classifications made by expert dietitians with those generated by an artificial intelligence model.

**Method:** A total of 49 YouTube videos that met the inclusion criteria were analyzed. The video characteristics were evaluated in relation to the view count, number of likes and comments, video duration, and time elapsed since upload**.** The quality of information provided in the video was assessed using the Modified DISCERN instrument, JAMA Benchmark Criteria, and Global Quality Score (GQS). A study-specific Binge Eating–Related Scoring System (BERS), consisting of 15 dichotomous items and based on video transcripts, was independently applied by both expert dietitians and the Gemini 3 Pro artificial intelligence model. In addition, 89,240 user comments were analyzed using R-based sentiment and emotion analysis techniques. Google Trends data for 2021–2026 were also evaluated. Statistical analyses were performed using SPSS 22.0.

**Results:** The median number of views was 2,043,167 (IQR: 1,043,285–5,550,269). AI-based BERS scores showed significant positive correlations with the number of views ($r=0.471$), likes ($r=0.453$), comments ($r=0.423$), and video length ($r=0.543$) ($p<0.05$). A moderate positive correlation was found between expert-rated and AI-generated BERS scores ($r=0.577$, $p<0.001$). Higher binge eating–related scores were negatively correlated with educational quality scores (GQS). Sentiment analysis revealed that 41.3% of comments were positive, and the most frequently identified emotions were trust and joy. Google Trends indicated a peak in "extreme diet" searches in 2026.

**Conclusion:** Highly engaging YouTube content often not only normalizes extreme eating behaviors but is also received positively by viewers. AI proved to be moderately reliable for identifying binge eating-related features, thus suggesting its potential as a scalable screening tool for monitoring harmful health trends. Interdisciplinary collaboration is required to ensure that AI-powered content analysis aligns with public health priorities.

**Keywords:** Nutrition, artificial intelligence, binge eating disorder, social media, YouTube.

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**Yapay Zekânın Riskli Yeme Anlatılarını Belirlemedeki Güvenilirliği: YouTube Radikal Diyet Videolarının Karşılaştırmalı Analizi**

**Öz**

**Amaç:** Bu tanımlayıcı çalışma, "extreme diet" ve "diet challenge" anahtar kelimeleri ile paylaşılan YouTube videolarında tıkınırcasına yeme ile ilişkili özelliklerin varlığını değerlendirmek ve uzman diyetisyenler tarafından yapılan sınıflandırmalar ile bir yapay zekâ modeli tarafından oluşturulan sınıflandırmaları karşılaştırmak amacıyla yapılmıştır.

**Yöntem:** Dahil edilme kriterlerini karşılayan toplam 49 YouTube videosu analiz edilmiştir. Videoların görüntülenme sayısı, beğeni sayısı, yorum sayısı, süresi ve yüklenme tarihinden itibaren geçen süre kaydedilmiştir. Bilgi kalitesi Modifiye DISCERN aracı, JAMA (Journal of the American Medical Association) kriterleri ve Küresel Kalite Skoru (GQS) kullanılarak değerlendirilmiştir. Çalışmaya özgü 15 maddelik Tıkınırcasına Yeme ile İlişkili Puanlama Sistemi (BERS), uzman değerlendiriciler ve Gemini 3 Pro yapay zekâ modeli tarafından (video transkriptleri üzerinden) bağımsız olarak uygulanmıştır. Ayrıca 89.240 kullanıcı yorumu R programlama dili kullanılarak duygu ve duygu durumu analizi yöntemleriyle incelenmiştir. 2021–2026 yıllarına ait Google Trends verileri de değerlendirilmiştir. İstatistiksel analizler SPSS 22.0 programı ile gerçekleştirilmiştir.

**Bulgular:** Medyan görüntülenme sayısı 2.043.167 (IQR: 1.043.285–5.550.269) olarak bulunmuştur. Yapay zekâ temelli BERS puanları ile görüntülenme (r=0,471), beğeni (r=0,453), yorum sayısı (r=0,423) ve video süresi (r=0,543) arasında istatistiksel olarak anlamlı pozitif ilişki saptanmıştır (p<0,05). Uzman ve yapay zekâ BERS puanları arasında orta düzeyde pozitif korelasyon belirlenmiştir (r=0,577, p<0,001). Tıkınırcasına yeme ile ilişkili daha yüksek puanların eğitimsel kalite (GQS) ile negatif ilişkili olduğu görülmüştür. Duygu analizinde yorumların %41,3'ünün pozitif olduğu; en sık belirlenen duyguların güven ve sevinç olduğu saptanmıştır. Google Trends verileri, 2026 yılında "extreme diet" aramalarında zirveye ulaşıldığını göstermiştir.

**Sonuç:** Yüksek etkileşim alan YouTube içerikleri, aşırı yeme davranışlarını normalleştirebilmekte ve izleyiciler tarafından olumlu algılanabilmektedir. Yapay zekâ sistemi, tıkınırcasına yeme ile ilişkili özelliklerin belirlenmesinde orta düzeyde güvenilirlik göstermiş olup zararlı sağlık anlatılarının izlenmesinde ölçeklenebilir bir tarama aracı olarak potansiyel sunmaktadır. Yapay zekâ destekli içerik analizinin halk sağlığı öncelikleri ile uyumlu hale getirilmesi için disiplinler arası işbirliği gereklidir.

**Anahtar Sözcükler:** Beslenme, yapay zekâ, tıkınırcasına yeme bozukluğu, sosyal medya, YouTube.

## Introduction

In recent years, there has been a rapid rise in the use of digital resources to meet a wide range of needs; these include seeking advice, entertainment, cooking, and coping with daily stress[1]. For many individuals, the internet, particularly social media platforms, has taken on the role of being the primary source for health-related guidance, lifestyle information, and nutrition advice[2]. YouTube is one of the most widely used platforms, with over two billion active users globally. It has become increasingly influential in disseminating advice, daily routines, and personal experiences through video blogs (vlogs) and user-generated content[2,3]. Video-sharing platforms such as YouTube facilitate seamless access to fitness, dieting, body image, and lifestyle-related content. Young adults frequently state that they use YouTube for health and nutrition advice, referencing its instructional and relatable format[4]. Although social media has been used in nutrition and health promotion interventions, there is growing evidence that suggests frequent exposure to diet- and body-focused content can be associated with adverse outcomes[5,6]. A systematic review indicates that particularly among adolescents and young adults, there is a significant association between social media use and eating disorders, including restrictive eating and binge eating[7]. Consequently, while social media can be used to promote healthy behavior, repeated exposure to extreme dietary practices may normalize harmful eating patterns[7,8].

Binge eating disorder (BED) is characterized by recurrent episodes of consuming large amounts of food within a short period; this is accompanied by loss of control and psychological distress, while there is no compensatory behavior[9]. Extreme dieting, which is also considered to be an eating disorder, involves severe restriction and rigid control of food intake, or prolonged fasting, and most often is pursued to ensure rapid weight loss or body modification. Such practices are associated with significant psychological and physiological risks and have been closely associated with body dissatisfaction or maladaptive weight-control motivations[10]. It is important to note that YouTube diet videos frequently frame extreme practices, such as prolonged fasting, not just as health strategies, but also as morally commendable or disciplined behavior, thus potentially legitimizing eating patterns that are highly restrictive[11].

It is thought that exposure to video content related to eating that is found on platforms such as YouTube can influence the eating attitudes and behavior of the audience[12]. Studies that examine content that is focused on eating, including videos that portray excessive consumption or restrictive practices, indicate that repeated exposure may not only normalize problematic behaviors but also shape perceptions of what is acceptable conduct regarding diet[13,14]. These findings raise concerns that diet-related video trends may contribute to the development of unhealthy eating behaviors, particularly among young and vulnerable audiences[1,12].

Diet-related content on YouTube is widespread; as a result it is important not only to examine the messages conveyed in these videos, but also to evaluate the tools that have been used to analyze the content. Although the use of artificial intelligence (AI) in health-related research has increased, there are still questions regarding how reliable AI-based analyses are and how much they align with expert human evaluation. Previous studies have reported substantial but imperfect concordance between AI classification systems and human raters, highlighting the need for further validation before there can be a large-scale application of AI systems in this area.

Although previous research has evaluated the quality of YouTube content related to specific eating disorders, such as avoidant/restrictive food intake disorder (ARFID), these studies have relied primarily on human assessment[11,15]. There is little evidence whether AI-based tools can identify risky or extreme diet-related narratives as reliably as human-based judgment.

In this study, the aim was to evaluate themes related to eating disorders in YouTube videos that have been shared under the keywords “extreme diet” and “diet challenge,” and to compare classifications made by a registered dietitian and that of the Gemini 3 Pro artificial intelligence model using a structured binary scoring system. A secondary objective was to assess the agreement and potential applicability of AI-based tools for identifying risky eating-related content on social media platforms.

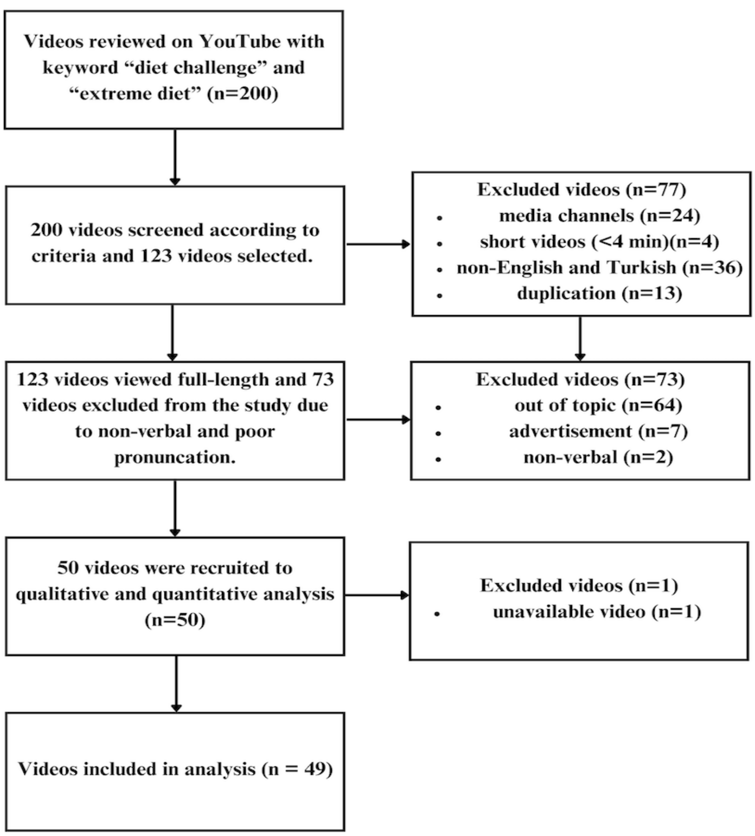
## Material and Methods

### *Search strategy*

Video selection was conducted independently by two dietitian researchers on YouTube in October 2025 using newly created accounts to reduce algorithmic and user-related biases. Searches were performed using the keywords "extreme diet" and "diet challenge." Videos published within the past five years, presented in English or Turkish, lasting at least four minutes, and uploaded by individual content creators were included. Promotional, duplicated, irrelevant, or non-eligible videos were excluded.

For each keyword, the first five pages of search results were screened, as users typically interact with content appearing on initial result pages (20 videos per page×5 pages=100 videos)[16,17]. Videos were sorted by view count, resulting in an initial pool of 200 videos. Of these, 50 met the inclusion criteria; however, one video later became unavailable, leaving a final sample of 49 videos. The selection process is illustrated in Figure 1.

**Figure 1.** Flowchart of the video selection process



### *Video characteristics*

In evaluating the videos, the number of views, likes, and number of comments, video length (seconds), time since upload days and comment content were taken into account. These variables were included in the analysis to reflect the level of video engagement and user interaction.

### *Reliability, validity, and quality assessment*

The Modified DISCERN (mDISCERN) instrument was used to evaluate the quality and comprehensiveness of the videos. This tool includes five criteria assessing whether the video is clear and understandable, based on reliable sources, presents balanced information, provides additional references, and addresses areas of uncertainty. Each item is scored dichotomously (1=yes, 0=no), yielding a total score ranging from 0 to 5, where higher scores indicate better quality and comprehensiveness of the content[18].

The Journal of the American Medical Association (JAMA) Benchmark Criteria were used to assess the reliability and quality of the medical information based on four components: authorship, attribution, disclosure, and currency. Each criterion received one point, resulting in a total score of between 0 and 4. Scores of 0–1 indicate insufficient information, 2–3 partially sufficient information, and 4 high-quality information[19].

To evaluate the overall educational quality of the videos, the Global Quality Score (GQS) was used. With this scale the clarity, quality, and usefulness of information was assessed using a five-point Likert scale, where 1 represents poor quality and minimal educational value and 5 represents excellent quality with high educational value[20].

All videos were independently evaluated by two researchers using these three assessment tools. Discrepancies between raters were resolved through discussion and consensus.

### **Sentiment–emotion analysis of videos with R programming language**

Sentiment analysis of comments from 49 YouTube videos related to “diet challenges” and “extreme diets” was conducted using the R 4.5.0 statistical programming environment. User comments stored in JSON Lines (.jsonl) format were analyzed using natural language processing (NLP) techniques. JSONL files were imported using the jsonlite package[21], merged into a single dataset, and only the text variable containing comment content was included in the analysis.

Text tokenization and sentiment classification were performed using the tidytext package[22]. Comments were tokenized with the unnest_tokens() function, and only alphabetic words consisting of at least three characters were retained. Text cleaning and data manipulation were conducted using the dplyr and stringr packages[23,24].

A two-stage stop-word filtering procedure was applied. First, the standard English stop-words from the list in tidytext were removed[18]. Second, commonly used but contextindependent YouTube comment terms (e.g., "video," "watch," "day," "people," "bro," "gonna," and "ate") were excluded using a manually created extended stop-word list. After preprocessing, a total of 89,240 comments were included in the analysis.

Sentiment classification was conducted using the AFINN lexicon, which categorizes text as positive, negative, or neutral. Emotional categories such as anger, sadness, fear, and joy were identified using the NRC lexicon. Visualization of results was performed with the ggplot2 package[25]. The most frequent words were presented using two visualization approaches: a bar plot displaying the ten most frequent words and a word cloud generated from word frequencies. In the word cloud, only words above a minimum frequency threshold were included, and word size was scaled proportionally to frequency[26]. The maximum number of displayed words was limited and the Dark2 palette from RColorBrewer was applied to improve visual clarity[27].

All text mining, sentiment analysis, and visualization procedures were conducted in R using the *jsonlite, dplyr, stringr, tidytext, ggplot2, wordcloud*, and *RColorBrewe*r packages[21-27].

### *Study-specific binge eating–related scoring system (BERS)*

Since mDISCERN, GQS, and JAMA benchmark criteria do not specifically evaluate binge eating–related characteristics in social media videos, a study-specific scoring system was developed to assess excessive consumption framing, behavioral modeling, triggering narratives, and health-related messaging in videos identified using the keywords "extreme diet" and "diet challenge." The BERS framework was designed to identify content features that may normalize or encourage maladaptive eating behaviors rather than to diagnose eating disorders. Development of the scoring system was informed by a targeted review of literature on binge eating–related behavioral indicators[7,28] and adapted from previously published topic-specific content analysis approaches used in video-based research[29] (Table 1).

The checklist consisted of 15 criteria, each scored dichotomously (1=present, 0=absent) based on verbal or visual presentation within the video. Total scores were analyzed using K-means clustering to classify videos into three groups representing lower, moderate, and higher levels of binge eating–provoking content.

Prior to the main analysis, a pilot assessment was conducted in which three researchers independently scored three videos, while the same videos were evaluated by the Gemini AI tool using identical scoring criteria. Partial agreement between human and AI scores supported proceeding with the main analysis.

All videos were independently evaluated in the main study by three researchers who used the BERS checklist. To avoid any possible bias, separate AI-based scoring was carried out by a fourth researcher who used Gemini to evaluate only the transcripts of the videos.

A structured Python-based workflow was used to score the video transcription and AI scoring. Audio streams were extracted with yt-dlp and processed by FFmpeg. Faster-Whisper (Large-V3) model was used for automatic speech recognition; predefined parameters (beam size=5, float16 precision, temperature schedule 0–0.4, and voice activity detection enabled) were used to accomplish this. Transcripts were stored as plain text and time-stamped JSON segment files, while a manifest system was used to record processing steps and outputs.

BERS scoring was carried out with the Gemini 3 Pro Preview model using standardized instructions. Each transcript was evaluated independently, and all 15 BERS items were scored dichotomously (0/1). Model parameters were fixed (temperature=0.1, top_p=0.95, thinking level=high), while structured JSON outputs were enforced so that there would be consistent formatting across evaluations.

Thus, each video received both researcher-derived and AI-generated BERS scores; the relationship between these scores was examined during statistical analysis.

**Table 1.** Binge Eating–Related Scoring System (BERS)

| | |
|---|---|
| **1** | Does the video present excessive consumption as an achievement, performance, or challenge? |
| **2** | Are extremely high calorie amounts emphasized in an enthusiastic or celebratory manner? |
| **3** | Is excessive eating framed as easy, repeatable, or normalized within the video narrative? |
| **4** | Is the eating episode described using highly sensory or exaggerated praise? |
| **5** | Is loss of control over eating explicitly expressed? |
| **6** | Are contextual triggers related to eating behavior presented? |
| **7** | Is reward-based eating language used? |
| **8** | Is the rapid consumption of large quantities emphasized? |
| **9** | Is the continuation of eating despite physical discomfort described? |
| **10** | Are feelings of shame, guilt, or regret explicitly expressed? |
| **11** | Are compensatory physical activities presented as a response to consumption? |
| **12** | Are compensatory behaviors related to eating implied or stated? |
| **13** | Does the video include a direct call for imitation by the audience? |
| **14** | Is escalation or intent to increase the intensity of consumption presented? |
| **15** | Is body weight or body-related outcome explicitly emphasized? |

Questions were answered as yes or no, yes = 1-point, no = 0-point



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### *Ethical Statement*

Ethical considerations were observed throughout the study. User anonymity was maintained and no personally identifiable information was collected or reported. All analyses were conducted in accordance with the relevant ethical guidelines for the use of user-generated online content.

### *Statistical Analysis*

Statistical analysis was performed using SPSS software (version 22, SPSS Inc., Chicago, IL, USA). The Shapiro-Wilk test was used to establish distributional properties of the variables. As none of the continuous variables demonstrated a normal distribution, the data were expressed as the median and interquartile range (IQR). Spearman's rank correlation analysis was used to examine relationships between quantitative variables. K-means clustering analysis was applied to identify distinct groups within the dataset. A p-value of less than 0.05 was considered statistically significant.

## Results

The general characteristics of the evaluated videos are presented in Table 2. According to the table, the median values (interquartile range (IQR)) for total views, likes, and comments were 2,043,167 (1,043,285–5,550,269), 68,441 (27,120–125,465) and 3,014 (1,446–6,136) respectively. The median video length was 1,099 seconds (858–1,491), and the median time since upload was 1,371 days (650–1,799).

**Table 2.** General characteristics of videos

| | **Median (IQR)** | **Mean ± S.D.** |
|---|---|---|
| **Total Number of Views** | 2 043 167 (1 043 285–5 550 269) | 5 202 917.02 ± 8359237.84 |
| **Total Number of Likes** | 68 441 (27 120–125 465) | 125 895.76 ± 190742.27 |
| **Total Number of Comments** | 3 014 (1 446–6 136) | 7 731.43 ± 15303.3 |
| **Video Length (seconds)** | 1 099 (858–1 491) | 1 282.67 ± 714.78 |
| **Time Since Upload (days)** | 1 371 (650–1 799) | 1 211.22 ± 686.58 |

IQR: interquartile range

Table 3 presents correlations between video characteristics, sentiment scores, and the mDISCERN, JAMA, GQS, BERS, and BERS-AI scoring systems. In the BERS system, a weak positive correlation was observed between video length and BERS score ($r=0.323$, $p=0.024$). In the BERS-AI system, moderate positive correlations were found with the number of views ($r=0.471$, $p=0.001$), likes ($r=0.453$, $p=0.001$), comments ($r=0.423$, $p=0.002$), and video length ($r=0.543$, $p<0.001$). Time since upload showed a significant negative correlation with BERS-AI scores ($r=-0.355$, $p= 0.012$). BERS-AI scores were also positively correlated with positive (r=0.325, p=0.022), negative (r=0.342, p=0.016), and neutral (r=0.437, p=0.002) sentiment categories.

**Table 3.** Correlations between video features and sentiment scores with the mDISCERN, JAMA and GQS scoring systems.

| | **mDISCERN** | | **JAMA** | | **GQS** | | **BERS** | | **BERS-AI** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **r** | **p** | **r** | **p** | **r** | **p** | **r** | **p** | **r** | **p** |
| **Features of Videos** | | | | | | | | | | |
| Views | -0.093 | 0.525 | 0.056 | 0.701 | -0.050 | 0.733 | 0.247 | 0.087 | .471** | 0.001 |
| Likes | -0.057 | 0.697 | 0.008 | 0.954 | -0.048 | 0.742 | 0.201 | 0.165 | .453** | 0.001 |
| Number of Comments | -0.139 | 0.340 | -0.043 | 0.767 | -0.163 | 0.263 | 0.171 | 0.239 | .423** | 0.002 |
| Video Length | 0.149 | 0.307 | 0.003 | 0.986 | 0.082 | 0.576 | .323* | 0.024 | .543** | 0.000 |
| Time Since Upload | 0.137 | 0.349 | 0.088 | 0.547 | 0.207 | 0.153 | -0.130 | 0.373 | .355* | 0.012 |
| **Sentiments & Emotions** | | | | | | | | | | |
| Positive | -0.033 | 0.824 | -0.030 | 0.840 | -0.010 | 0.946 | 0.033 | 0.820 | .325* | 0.022 |
| Negative | 0.051 | 0.729 | -0.064 | 0.664 | -0.030 | 0.837 | 0.069 | 0.640 | .342* | 0.016 |
| Neutral | -0.166 | 0.256 | -0.175 | 0.230 | -0.244 | 0.090 | 0.203 | 0.162 | .437** | 0.002 |

r, Spearman's rho; *p < 0.05, **p < 0.01

mDISCERN: Modified DISCERN; JAMA: Journal of the American Medical Association; GQS: Global Quality Score; BERS: Binge Eating–Related Scoring System; BERS-AI: Binge Eating–Related Scoring System- Artificial Intelligence

The correlations between the DISCERN, GQS, BERS, and BERS-AI scoring systems are presented in Table 4. A statistically significant, moderate, positive correlation was observed between DISCERN and GQS scores (r=0.641, p<0.001). GQS scores showed a weak negative correlation with BERS scores (r=-0.297, p=0.038) and a moderate negative correlation with BERS-AI scores (r=-0.370, p=0.009). A statistically significant moderate positive correlation was identified between BERS and BERS-AI scores (r=0.577, p<0.001).

**Table 4.** Correlations between scores

| | DISCERN | | JAMA | | GQS | | BERS | | BERS-AI | |
|---|---|---|---|---|---|---|---|---|---|---|
| | r | p | r | p | r | p | r | p | r | p |
| DISCERN | 1.000 | - | | | | | | | | |
| JAMA | 0.202 | 0.163 | 1.000 | - | | | | | | |
| GQS | .641** | 0.000 | 0.208 | 0.151 | 1.000 | - | | | | |
| BERS | -0.086 | 0.555 | -0.060 | 0.680 | -.297* | 0.038 | 1.000 | - | | |
| BERS-AI | -0.160 | 0.272 | 0.043 | 0.769 | -.370** | 0.009 | .577** | 0.000 | 1.000 | - |

r, Spearman's rho; *p < 0.05, **p < 0.01

mDISCERN: Modified DISCERN; JAMA: Journal of the American Medical Association; GQS: Global Quality Score; BERS: Binge Eating–Related Scoring System; BERS-AI: Binge Eating–Related Scoring System- Artificial Intelligence

Figure 2 shows the distribution of the overall sentiment categories. Of all the comments analyzed, 41.3% (n=36,831) were classified as positive, 37.7% (n=33,629) as neutral, and 21.0% (n=18,780) as negative.

Emotion analysis based on the NRC lexicon revealed that the most frequently identified emotions were trust (11.78%, n=43,409) and joy (11.32%, n=41,742). This were followed by anticipation (9.52%), fear (8.21%), sadness (6.82%), anger (6.37%), disgust (5.96%), and surprise (5.15%).

**Figure 2.** Percentages of sentiments and emotions expressed in comments on videos

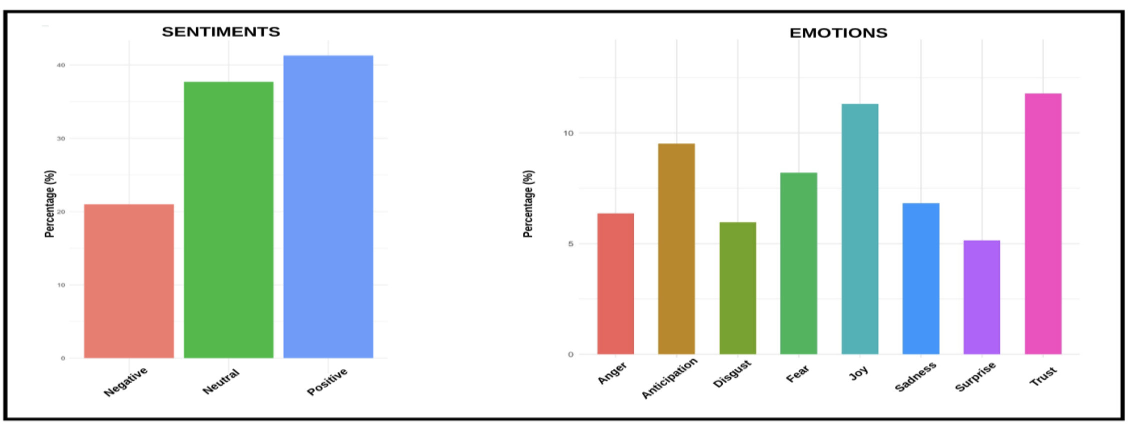



Figure 3 shows the most frequently used words in user comments. The most commonly used term was "eat" (n=8 329), followed by "food" (n=7 883), "diet" (n=5 526), and "love" (n=5 362). Other frequently used words included "eating" (n=4 832), "challenge" (n=3 481), "calories" (n=3 107), "weight" (n=3 048), "water" (n=3 011), and "feel" (n=2 315).

The word cloud visualisation (Figure 3) further demonstrates that terms such as “food”, “eat”, “diet,” “eating”, “challenge,” and “love” appeared prominently in the comment corpus.

**Figure 3.** The number of times words were used in the comments, and the Word cloud showing the most frequently used words in the comments

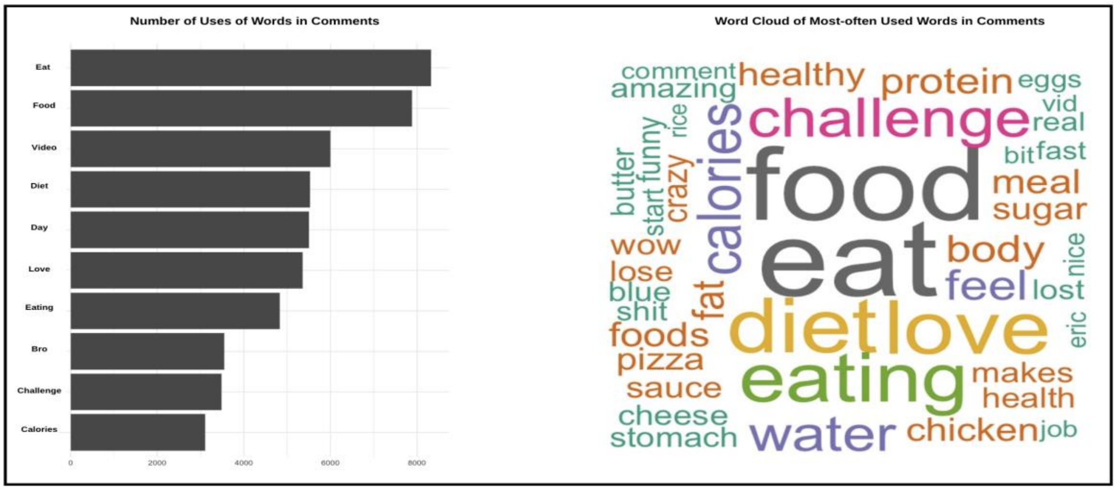
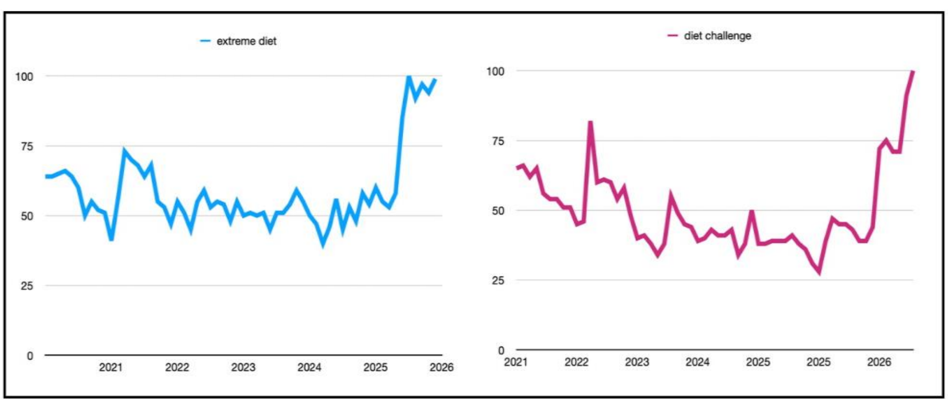



Figure 4 presents Google Trends data for the keywords “extreme diet” and “diet challenge” between 2021 and 2026. Search interest in the term “extreme diet” fluctuated between approximately 40 and 70 index points between 2021 and 2024. A marked increase was observed beginning in late 2025, with search interest reaching peak values close to 100 in 2026.

Similarly, search interest in “diet challenge” varied between approximately 30 and 70 index points from 2021 to 2024. A significant increase in search interest was observed towards the end of 2025, with the search index approaching 100 in 2026.

**Figure 4.** Increase in search keywords “extreme diet” and “diet challenge” on YouTube (https://trends.google.com)



## Discussion

This study evaluated YouTube videos that were shared under the keywords "extreme diet" and "diet challenge" by combining content quality measures, BERS, BERS-AI classification, and sentiment analysis. Overall, the findings suggest that it is possible that highly engaging diet-related content can normalize extreme eating behaviors. At the same time, AI-based systems demonstrate potential for large-scale monitoring although there is still a need for validation and human oversight[30,31].

Higher BERS-AI scores were associated with greater engagement (views, likes, comments, and video length), indicating that videos which have stronger characteristics related to binge eating tend to reach wider audiences. Previous research similarly shows that performative eating and exaggerated consumption are amplified by platform dynamics which prioritize viewing time and user engagement[13].

The fact that there is a negative correlation between time since upload and BERS-AI scores suggests that more recent videos have more characteristics related to binge eating. This finding is consistent with studies which link increased exposure to dieting and appearance-focused social media content with greater body dissatisfaction and the risk of developing eating disorders[10,32].

A moderate positive correlation was observed between DISCERN and GQS scores, indicating consistency between the educational quality indicators. However, there was a negative association for both BERS and BERS-AI with GQS; this suggests that videos which have a higher educational quality are less likely to include characteristics that might provoke binge eating. Similar findings have been reported in studies which demonstrate that evidence-based information does not necessarily have a correlation with YouTube popularity[13,33]. Moreover, the absence of a correlation between JAMA scores and binge eating–related scores indicates that structural transparency alone is insufficient to prevent the normalization of extreme eating behaviors[34].

Sentiment analysis showed that the majority of comments were positive or neutral, with trust and joy being the most frequently identified emotions. BERS-AI scores were positively associated with positive, negative, and neutral sentiments, thus suggesting that videos which have more characteristics related to binge eating create greater emotional engagement. Similar patterns have been observed in studies on mukbang and diet-related content, where problematic eating representations coexist with strong viewer approval[35,36]. Experimental research has also demonstrated that exposure to diet-focused or idealized body content can increase body dissatisfaction and unhealthy eating habits, particularly among young audiences[37,38].

The comparison between BERS and BERS-AI scores revealed a moderate positive correlation, indicating partial agreement between expert evaluation and AI-based classification. This finding is in keeping with previous research, demonstrating that AI systems are able to approximate human judgments in health-related content analysis but are unable to fully replace expert evaluation[39]. The differences most likely arise due to



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the visual and contextual cues that experts work from, whereas BERS-AI relies only on transcripts. Visual elements and editing styles may therefore influence behavioral modeling in ways that are not perceived through text-based analysis. These findings support the use of AI as a preliminary screening tool within a human-in-the-loop framework[34].

Overall, the results highlight a tension between platform engagement mechanisms and public health priorities. Videos that have more characteristics related to binge eating had higher engagement and produced more positive emotional responses; at the same time, educational quality indicators were inversely related to behavioral risk features. These findings reinforce concerns that social media popularity does not reliably reflect informational quality[30] and that repeated exposure to diet-focused content may increase the risk of developing eating disorders among young audiences[37]. Importantly, the study does not suggest that all diet challenges or extreme diet content are inherently harmful, but rather identifies narrative features which may increase vulnerability when repeatedly reinforced.

### *Strengths and Limitations*

This study seeks to integrate validated quality assessment tools, a theory-driven risk scoring system (BERS), AI-based classification (BERS-AI), and sentiment analysis. The comparison of expert ratings and AI outputs makes a significant contribution to research into the automated evaluation of digital health content. However, there are several limitations that should be noted. The sample size was relatively small and restricted to English and Turkish videos. Any causal interpretation is prevented by the cross-sectional design. The AI analysis relied only on transcripts and did not include visual or multimodal features, and only one AI model was applied. In addition, contextual nuances may not be captured by lexicon-based sentiment analysis.

Future research should include larger samples, use multimodal AI approaches, and adopt longitudinal designs to provide a better understanding of the potential behavioral impact of extreme diet-related content.

## Conclusion

It is possible that engaging YouTube videos of extreme dieting and diet challenges can normalize maladaptive eating behaviors. The association between higher BERS-AI scores and engagement metrics suggests that algorithmic visibility may amplify content depicting greater behavioral risk. Artificial intelligence had moderate agreement with human expert evaluation, thus indicating a potential for AI as a scalable screening tool to identify risky eating-related narratives; however, it is important to note that this application should complement—not replace—expert judgment. As digital platforms increasingly shape dietary norms, collaboration between nutrition science, public health, and AI is essential in order to create and support responsible health communication.

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