

# JOURNAL OF INFORMATION SYSTEMS APPLIED RESEARCH AND ANALYTICS

**Volume 19, No. 4**  
December 2026  
ISSN: 1946-1836

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JISARA is published online (<https://jisara.org>) in connection with the ISCAP (Information Systems and Computing Academic Professionals) Conference, where submissions are also double-blind peer reviewed. Our sister publication, the Proceedings of the ISCAP Conference, features all papers, teaching cases and abstracts from the conference. (<https://iscap.us/proceedings>)

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# JOURNAL OF INFORMATION SYSTEMS APPLIED RESEARCH AND ANALYTICS

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# Using a Large Language Model to Evaluate Content Quality in Nutritional YouTube Shorts

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## Abstract

This study assesses the quality of nutrition-related shorts on YouTube, focusing on the prevalence of credible content. Using Google Trends, we analyzed YouTube search behaviors for key nutrition terms over five years. We found peak years before and after Covid. Based upon Google Trends peak years, we developed python code using an API key to fetch YouTube shorts. A total of 2,391 YouTube shorts were fetched and further assessed for quality inclusion. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was utilized to illustrate the video selection process/parameters. Shorts were excluded based on duplicates, content, author channel credentials, duration, not in English, no words spoken or an ad. A remaining total of 30 videos were selected to be analyzed via Google AI Studio's Gemini 2.5 Pro Preview 05-20 regarding their reliability, quality of information, and overall quality using the DISCERN instrument. Results revealed only 6 of the selected shorts had an overall high-quality score. While this study is limited to YouTube and nutrition-related content, its findings offer valuable insights for health professionals, policymakers, and educators aiming to improve digital health literacy. It also adds practical value to technology educators teaching students to fetch data via an API and assessing the quality of data via LLM.

**Keywords:** Large Language Model, Quality Nutrition Content, DISCERN, YouTube, AI, PRISMA

**Recommended Citation:** Powell, L.M., Powell, G., Rebman Jr., C.M., Wimmer, H., (2026). Using a Large Language Model to Evaluate Content Quality in Nutritional YouTube Shorts. *Journal of Information Systems Applied Research and Analytics*, v19(n4) pp 53-69. DOI# <https://doi.org/10.62273/HFNS3900>

# Using a Large Language Model to Evaluate Content Quality in Nutritional YouTube Shorts

*Loreen Marie Powell, Gwendolyn Powell, Carl Michael and Hayden Wimmer*

## 1. INTRODUCTION

Over the last five years, the increase in use of social media and digital platforms amongst teens has shifted towards watching videos on interacting platforms (Aveiro & Sidoti, 2024; Vogels et al. 2022). YouTube, Instagram and Tik Tok are the top social media platforms used by teens. However, YouTube remains the most used platform amongst teens with nine in ten teens using the platform, and only six in ten teens use Instagram and Tik Tok (Aveiro & Sidoti, 2024).

Currently, there are several quality challenges regarding YouTube ranging from view fraud (Kuchhal and Li, 2022), and scams (Rajeshwari et al., 2024) to misinformation, (Molloy, et al., 2024; Hoffman et al, 2019), fear of missing out (FoMO) (Wijaya & Subroto, 2025), and mental health challenges (Leiner et al., 2025). Moreover, the artificial intelligence (AI) algorithm-driven content recommendations on the platform may wrongfully prioritize poor quality videos over high quality videos (Hoffman et al., 2019). Unfortunately, teens and adults alike are not aware of these challenges. For example, a recent study by Son et al. (2023) utilized YouTube as a self-education program designed for elderly diabetics in Hongcheon, Korea. In their cross-sectional study using a content participant analysis on the satisfaction of 38 diabetes care videos, averaging 7 minutes, in length. They found that 100% of the participants, regardless of the year they participated, reported satisfaction with the program and found the Youtube content helpful. However, while participants were satisfied, the quality of the video was unknown.

YouTube video content is also contributing to change. Today, many of the short-form video content on YouTube, also called shorts, are now watched more than regular videos (Violot et al. 2024) and are often cross platformed on Instagram Reels and TikTok. As a result, YouTube shorts are more accessible, interactive, and a promising means to engage with teens regarding health-related education (Bopp et al., 2019; Global Web Index, 2023; Hoffman et al., 2019; Malloy et al, 2024).

Many teens watch trendy Mukbang, or broadcast eating, shorts on YouTube (Jang et al., 2024) which promotes unhealthy eating habits. Additionally, YouTube is known to contain an excessive number of advertisements regarding high-calorie, low-nutrition foods which are targeted toward today's youth (Jang et al, 2024; Lee & Yoo, 2020).

Health habits established during the teen years can be consequential to future wellbeing (Malloy et al., 2024, Lawrence et al., 2020). Thus, it is essential to examine the quality of nutritional shorts on YouTube to provide data for governments to establish policies which may help regulate the quality of nutritional YouTube content for teens (Jang et al, 2024; Lee & Yoo, 2020).

Typically, health related YouTube videos are manually assessed for quality using the Health on the Net Foundation (HON) Code, the Journal of the American Medical Association (JAMA) tool, Global Quality Scale (GQC) method, and the DISCERN tool. These methods/tools are time intensive due to their manual assessment of the YouTube content. However, a recent study by Khalil et al. (2025) investigated the capacity of large language models (LLMs) to assess the quality of medical information presented in YouTube videos. They conclude that some LLMs may be used to assess the quality of YouTube.

A scholarly literature search via Google scholar, and the Marywood University academic databases revealed some existing studies evaluating the quality of YouTube videos. However, we did not find a study which examined nutritional YouTube shorts for quality nutrition information via an LLM. This paper will serve as the first study to examine Nutritional YouTube shorts for quality via a LLM. The remainder of this paper is organized as follows: brief literature review, goal, methods, results, conclusion with limitations, and future research.

## 2. LITERATURE REVIEW

Good nutrition is very important in maintaining a healthy mind and body (Malloy et al., 2024,

Lawrence et al., 2020; Smith & Lee, 2020; Wang & Gago 2024). Nutritional habits learned during adolescence form foundation for lifelong dietary habits (Malloy et al., 2024, Lawrence et al., 2020). As a result, it is best to provide adolescents with quality nutritional knowledge, skills, and confidence to make informed dietary choices as poor nutrition may lead to obesity and metabolic disorders which may have long-term health effects (Malloy et al., 2024; Roberts et al., 2021; Jones et al., 2019).

### **Overweight and Obesity**

Overweight and obese individuals consume more calories than they expend which leads to a build-up of excess fat. A healthcare provider will classify someone as obese if he or she has a body mass index (BMI) of 30.0-39.9 and severely obese if the BMI is 40 or greater. In comparison, a healthful BMI would be 18.5-24.9 (Obesity Action Coalition, 2025).

Currently, obesity among teenagers has reached alarming levels, with the CDC reporting that nearly 20% of youth aged 2-19 years are affected by obesity (U.S. Centers for Disease Control and Prevention (CDC), 2024). The COVID-19 pandemic exacerbated this issue, as studies observed a significant increase in obesity rates during this period due to an increase in sedentary lifestyle and unhealthy habits (Iacopetta et al., 2024; Wang and Gago, 2024; Zembrani et al., 2021).

### **Digital/Social Media Platforms**

Teens often turn to digital platforms like YouTube, TikTok, and Instagram for information, fun, and entertainment. Pew Research (2023) reports that teens use these platforms daily for hours. However, YouTube remains the most widely used platform, with nine out of ten teens utilizing it (Aveiro & Sidoti, 2024). This shift underscores the importance of these platforms in shaping teen behavior, including their health-related knowledge (Giovannelli et al., 2022).

Boté-Vericad (2025) examined YouTube search behaviors of Library and Information Science professors and students from Europe and Latin American countries. Specifically, they conducted a qualitative study using semi-structure interviews to collect data on 63 participants regarding YouTube searching behaviors. One result relates to our research. They found that YouTube acts as a supplementary learning resource for students and pedagogical enhancement tool for professors, imply that both

educators and students turn to YouTube to aid in learning.

One of the challenges of online platforms like YouTube is view fraud. Research by Marciel et al. (2016) highlights the prevalence of inflated view counts, which can mislead users into trusting low-quality or promotional content. This fraudulent activity undermines the credibility of educational resources. Teens are particularly vulnerable to scams on social media platforms. The FDA (2024) has documented numerous cases of health-related fraud targeting young users, such as false claims about dietary supplements. A study by Majerczak and Strzelecki (2022) emphasizes the importance of ensuring credibility to protect impressionable audiences from such scams.

### **Quality Standards for Health Information on the Internet**

The HON Code represents a standard for reliable online health information. Studies highlight its effectiveness in promoting credible and quality-assured content (Boyer et al., 1998). However, its adoption among YouTube health educators remains limited, suggesting the need for broader implementation and awareness campaigns to enhance the reliability of health information available to teens.

The HON Code was a standard designed to certify reliable online health information. Established in 1995, the HON Code aimed to improve the quality of health content on the internet by encouraging transparency, evidence-based information, and ethical practices (Boyer et al., 1998). Studies highlighted its effectiveness in promoting credible and quality-assured content. However, the HON Code initiative was discontinued in 2022 due to funding challenges and the growing complexity of the digital health landscape.

Powell et al. (2025) modified and combined concepts from the HONCode and the National Institute on Aging's Quality Resource website (<https://www.nia.nih.gov/health/healthy-aging/how-find-reliable-health-information-online>), to create a new framework to assess online health information for quality. They utilized the Delphi approach of experts to develop and test their framework. However, there has not been any study found which utilizes their newly created framework.

The Office of the Surgeon General (n.d.). provides a simple five-step health misinformation checklist. The check list encourages checking the CDC website, looking for healthcare professional credentials, searching and reading about the person or organization making the claim, and if unsure, don't share the information with others. Their checklist is similar to Powell et al.'s (2025) framework but, not as comprehensive.

There have been additional studies which utilize the JAMA tool, the GQC method, or their own method for selecting quality videos. For example, Gimenez-Perez et al (2020) developed their own method to evaluate the quality of educational YouTube videos on type 2 diabetics. They evaluated quality by video content, not specified as an ad, non-English language, no words, and the duration of the video. Additionally, Sütçüoğlu et al. (2023) utilized four methods (DISCERN, JAMA, GQC, and a modified DISCERN) to evaluate scientific reliability and quality of YouTube videos on cancer and nutrition.

DISCERN is another standardized, reliable tool designed to assess the quality of written consumer health information. Its development involved a rigorous process that included input from health professionals and patients, resulting in a 16-item questionnaire that is both comprehensive and user-friendly. The tool demonstrated strong inter-rater reliability and internal consistency, making it suitable for both academic research and clinical settings. One of DISCERN's key strengths is enabling users to critically appraise sources based on transparency, relevance, and evidence-based content (Charnock et al., 1999). Due to its validity, ease of use, and applicability across various formats of health communication, DISCERN has been widely adopted in research evaluating the quality of online health information (Khalil et al. 2025). As a result, DISCERN is a valid instrument commonly used as a benchmark for ensuring that patients and the public can access high-quality, trustworthy health resources.

One challenge with the DISCERN process is that an expert must manually assess each video. Thus, it is difficult to ensure that the expert is paying attention to every part of the video to properly assess it. Furthermore, this is a time intensive process. As a result, many studies debate the quality of the manual process (Khalil et al., 2025).

### Goal and Research Questions

The goal of this research is to assess the quality of nutritional videos for teens on YouTube. Specifically, we seek to answer the following research questions:

1. What is the best timeframe relative to YouTube search behaviors for fetching nutrition related content?
2. What is the overall percentage of selected/included shorts considered to be worthy of DISCERN evaluation via Gemini 2.5 Pro?
3. What is the overall percentage of quality nutrition related shorts on YouTube as defined by Gemini 2.5 Pro using the overall DISCERN score?

### 3. METHODOLOGY

To accomplish our research goal, we first need to evaluate the number of relative YouTube search behaviors regarding healthy nutrition. To do this, we utilized Google Trends.

Google Trends (<https://www.google.com/trends/>), is a free and open access website which provides insights into the popularity of specific search terms, timeframes and geographical locations. It allows users to analyze patterns for Google and YouTube search behaviors. Additionally, it allows comparisons between multiple search terms, which is useful for identifying relative popularity and emerging patterns (Nuti et al., 2014).

The versatility of Google Trends makes it a valuable research tool. For example, Nuti et al (2014) conducted a systematic review of 70 published health-related research studies in which Google Trends utilized from 2008- 2013. They found that there was an increase in usage for health-related research to monitor and understand societal search behaviors. More recently, Gimenez-Perez et al. (2020) utilized Google Trends to better understand current YouTube search behaviors of current users.

The Google Trends exploration for this study took place on January 2, 2025. We enabled Google Trends to view data for the USA and the World separately. We also enabled the timeframe of Google Trend included in the past 5 years to see the search behaviors over an extended period, as well as the pre, post, and the recent health pandemic period. Table 1 contains the criteria and search terms used in our Google Trends search.

|                     |                                                                            |
|---------------------|----------------------------------------------------------------------------|
| <b>Locations</b>    | Worldwide                                                                  |
|                     | United States                                                              |
| <b>Time Frames</b>  | Customized                                                                 |
|                     | Pre + COVID + Post<br>(1/1/2017 – 12/31/2024)                              |
|                     | Pre Years<br>(1/1/2017 – 12/31/2019)                                       |
|                     | COVID Peek Years<br>(1/1/2020 – 12/31/22)                                  |
|                     | Post Peek Years<br>(1/1/2023 – 12/31/2024)                                 |
| <b>Topic</b>        | Health                                                                     |
| <b>Search</b>       | YouTube                                                                    |
| <b>Search Terms</b> | Nutrition + Nutritional Facts +<br>Nutritional Value + Nutritional<br>Food |

**Table 1: Google Trends Search Criteria**

#### Video Selection Process and Parameters

Based upon the results of the Google Trends, we selected to fetch YouTube shorts created between the post COVID-19 timeframe of 01/01/2023 – 01/01/2025 because it yielded the highest trends. This is later explained in the results section. Table 2 provides all the parameters used to pull the videos. These parameters are consistent with previous research studies that pulled YouTube videos for research (Aydin et al., 2020; Gimenez-Perez et al., 2020; Altun et al., 2022, Gulve et al. 2022; Dobosz et al, 2023).

|                                                                                                                       |
|-----------------------------------------------------------------------------------------------------------------------|
| <b>Parameters</b>                                                                                                     |
| To exclude ads in the search query                                                                                    |
| To only fetch short videos                                                                                            |
| To fetch only those videos published after defined start date and end date<br>(01/01/2023 – 01/01/2025)               |
| To fetch only those videos that prioritize English-language                                                           |
| To fetch videos via our 4 search terms<br>("Nutrition", "Nutritional Facts", "Nutritional Food", "Nutritional Value") |
| To fetch video details (keywords, video title, channel title, URL, and duration in minutes)                           |

**Table 2: Parameters Used in Our Code to Pull the YouTube Data**

Next, we created a YouTube data API v3 key using the Google Cloud Developer Console (<https://console.cloud.google.com>). Once we had the API key, we opened Jupiter Notebooks within Anaconda Cloud

(<https://anaconda.cloud/>) and created code using our coding knowledge. It is also important to note that some assistance was used from Anaconda's AI Assistant 4.33.0 for writing the code regarding pulling only shorts (Anaconda, Inc. (2025). The goal of our code was to utilize the specific parameters identified from the Google Trends results and pull YouTube videos in a comma separated value (csv) output. Table 3, listed in Appendix A, contains the code used for this study. Please be aware that for security reasons, we removed our API key from the code presented in table 3.

Our code was executed, and the results were produced in Anaconda Cloud in a csv file. We exported the csv file and imported it into Microsoft (MS) Excel. Here the videos were filtered and manually examined to ensure that all selection parameters were met. Additionally, duplicates were removed, and the videos were filtered by Channel credentials. We chose to filter by channel because Carlson et al. (2023) highlight that incorporating titles such as "Dr" or "Doctor" in a YouTube channel name serves as a means for content creators to signal professional expertise. Additionally, they stated that current guidance from professional licensing boards emphasizes the importance of transparency in sharing credentials on social media platforms. As such, they examined 506 health-related videos for Channel credential disclosure and found that 46.6% of channels disclosed their academic degree, 39.7% reported their specialty, and only 16% indicated their level of training.

Based upon Carlson etl al.'s (2023) findings, our channels were filtered by academic degree, and specialty. Specifically, channels which did not contain Medical Doctor (MD), Doctor of Medicine (Dr.), and Register Dietitian (RD) initials or credentials were excluded. Among those channels which did contain MD, Dr, or RD, a manual examination of videos was performed to exclude videos based upon if they were not in English, voiceless, did not have relevant content to human nutrition, and had a duration time more than one minute. It is important to note that there have been many previous studies which utilized similar exclusion criteria (Aydin et al., 2020; Gimenez-Perez et al., 2020; Altun et al., 2022, Gulve et al. 2022; Dobosz et al, 2023).

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework was used to systematically document the video selection process and associated parameters. This method provided a transparent

account of the exclusion criteria used during the screening phase, culminating in the final set of YouTube Shorts to be transcribed and analyzed for quality based upon the DISCERN method.

### Video Transcription Extraction

YouTube's subtitles and captions "often lack punctuation and capitalization and contain errors" (Khalil et al. 2025). Therefore, we did not use YouTube's automatically generated subtitles for transcript generation. Instead, we utilized a cloud-based application called Descript App 2.6.0. We individually uploaded each selected YouTube URL into the Descript app to extract the audio and generate transcripts for each individual YouTube short. Each transcription was placed into a coordinating cell within an Excel workbook.

### Video Quality Examination

While there are many ways to evaluate information for quality, we selected to use the DISCERN instrument. As previously stated, the DISCERN instrument is a well-established, generic evaluation tool for assessing quality. It has 16 questions and is divided into three sections. Specifically, the reliability of the publication section (questions 1–8), evaluates clarity of aims, relevance, sources of information, and transparency of potential biases of the content. The quality of information about treatment choices section (questions 9–15), examines whether risks, benefits, and alternatives are presented in a balanced and comprehensive manner. Finally, Overall quality rating section (question 16), provides a global judgment of the publication's quality. Each question is scored on a 5-point Likert scale (1 = low quality, 5 = high quality). A higher total score indicates greater reliability and quality (Khalil et al, 2025).

A LLM by Google's AI Studio's Gemini 2.5 Pro was utilized to assess the quality of the 30 selected YouTube videos using the DISCERN Instrument. Gemini 2.5 Pro was selected rather than a human expert because in a recent study by Khalil et al (2025), they compared evaluation results of LLMs and human experts on medical YouTube videos 10 minutes in length via the DISCERN instrument. They found that some LLMs, such as Gemini 1.0 Pro, are capable of effectively evaluating the quality of medical videos in almost perfect agreement with human experts. Their study is in line with previous studies such as Karabacak et al (2023) which suggested that LLM has this potential.

This study employed one zero-shot prompting. Zero-shot learning refers to the ability of machine learning models to perform tasks without access to labeled data specific to the target task, instead leveraging knowledge acquired from unrelated or previously learned tasks (Karabacak et al., 2023; Khalil et al., 2025; Xian et al., 2019). Additionally, a recent study by Khalil et al. (2025) found no significant difference in outcomes between zero-shot prompting and guided scoring prompting for majority of DISCERN questions. Figure 1 provides the zero-shot prompt used in Gemini Pro. Data resulting from the zero-shot prompt was exported to a single table in Microsoft Excel and analyzed.

**Figure 1 Zero-shot prompt used in Gemini**

You are a medical expert. Rate each of the following 30 Transcripts of a Nutrition Related YouTube videos according to all 16 DISCERN questions.  
Please return an integer score ranging from 1 to 5 where 1 means "no, 3 means "partially", and 5 means "yes". Then explain your choice.

Please place all answers in one comprehensive organized table for all 30 videos for each DISCERN question.  
(Followed by text transcriptions for all 30

## 4. RESULTS

Within a specified time frame, Google Trends normalizes the search data on a scale from 0 to 100 with peak search interest represented with 100. Figure 2 shows the results from our Google Trends Worldwide YouTube searching report from 01/01/2017 to 12/31/2024 for key terms (Nutrition, Nutritional Facts, Nutritional Value, and Nutritional Food) show a peak before and after COVID, but not necessarily during COVID.

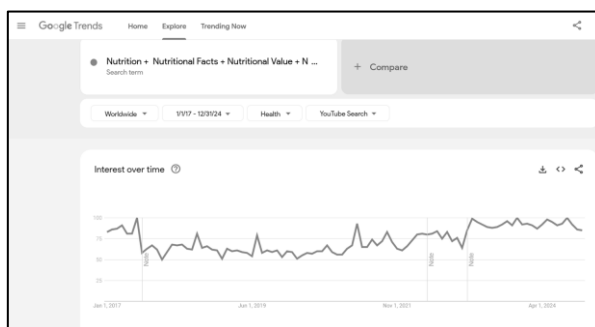


**Figure 2 Google Trends output for key terms from 01/01/2017 – 12/31/2024**

(Data source: Google Trends  
<https://www.google.com/trends> accessed  
January 6, 2025)

Upon closer assessment of the Google Trends Worldwide search based upon regions, we found that out of the 193 regions identified by Google Trends for our search, the United States is within the top percentage. Figure 3 demonstrates how the United States is 33 out of the 193 regions.



**Figure 3 Google Trends Search Results by Region** (Data source: Google Trends  
<https://www.google.com/trends> accessed  
January 6, 2025)

Based upon the results in Figure 3, we further looked at the United States results. Figure 4 illustrates a better identified peak for our search terms prior to COVID. Additionally, there is a noticeable decrease in searching for our key terms during COVID. However, there is a peak post COVID.

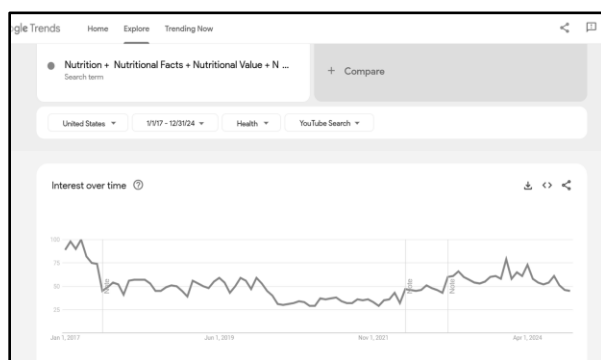


**Figure 4 Google Trends Search Results by United States** (Data source: Google Trends  
<https://www.google.com/trends> accessed  
January 6, 2025)

Based upon the results shown in Figures 2, 3, and 4, we pull worldwide data within the post-COVID years. It was not necessary to pull data

during the COVID time frame as there were not as many people searching for our specific terms. Thus, on January 7, 2025, we utilized our python code in anaconda cloud to fetch YouTube videos. A total of 2,391 YouTube videos, based upon the parameters, were pulled. The parameters were previously listed in table 2 and within our code previously listed in table 3 within Appendix A. Among those videos, 191 duplicates were removed. This left us with 2,200 videos filtered by channel criteria and manually assessed.

A total of 30 videos remained after the selection criteria evaluation. Specifically, after applying the filters for "RD" and conducting a manual assessment of quality criteria, 6 items remained, while 25 items remained following the application of filters for "MD" and "Dr" and the same manual assessment process. A PRISMA flow diagram, illustrating the process of how we came to 30 quality videos, is presented in Appendix B.

Table 4 presented in Appendix C provides details regarding the remaining 30 shorts which were accessed via DISCERN using Gemini 2.5 Pro. Here we can see that majority of the shorts pulled were from the USA. Additionally, 56.67% of the shorts pulled are cross channeled with either Instagram and/or TikTok.

### Overall Quality

Table 5, in Appendix D, contains the LLM results for each DISCERN question. As previously stated, the DISCERN instrument consists of 16 questions, divided into three sections. Each question is scored on a 5-point Likert scale (1 = low quality, 5 = high quality). A higher total score indicates greater reliability and quality.

Question 16 (Q16) of the DISCERN tool provides an all-inclusive evaluation of each short's overall quality. This question provides a summative rating that reflects both the reliability of the information, and the quality of guidance provided on treatment choices. Q16 reflects the extent to which a video can be considered a trustworthy and comprehensive resource for individuals seeking to make informed health decisions.

As shown in figure 6, the score results from our Gemini 2.5 Pro results ranged from 1 to 5, with most videos receiving a score of 1 or 3, indicating low to moderate quality. Specifically, only 6 shorts (shorts 21–26) received the maximum rating of 5. This suggests that only 20% of the shorts consistently provided clear,

comprehensive, balanced, and well-referenced information. Thus, they are considered quality shorts.

Also shown in figure 6 a total of 10 shorts (shorts 4, 6, 7, 11, 14, 15, 27, and 28) or 33% received a score of 3 for question 16 (Q16). A rating of 3 represents a moderate level of overall quality. A DISCERN score of 3 suggests that while these videos may be somewhat informative and provide a general overview, they fall short in terms of depth, evidence-based rigor, and completeness. They may serve as an introductory resource but are insufficient as standalone tools for informed nutrition-related decision-making.

Finally, at the lower end of the quality spectrum, 14 out of thirty shorts or nearly 47% of the data sample received a score of 1 for Q16. A score of 1 on this item reflects fundamental and pervasive deficiencies across both reliability and treatment-related informational domains. Specifically, this low score indicates very poor overall quality.

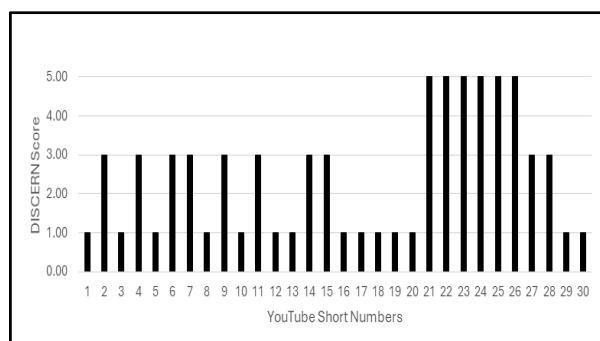


**Figure 6 Overall Quality (Q16) of Nutrition Related YouTube Shorts**

In the context of the DISCERN tool, a reliability score refers to how well a piece of health information (like a website or publication) meets criteria for being a reliable source of information, particularly regarding treatment options. Figure 7 shows that the average reliability score is 3.5 or lower. Obviously, the shorts, which had an overall quality score of 5, also had the highest overall average reliability score of 3.5. Additionally, one other YouTube short (Number 2) had an overall average score of 3.5. The remaining shorts had an overall average reliability score of less than 3.5.

These results suggest that the majority of YouTube shorts evaluated in this study did not meet a high standard of reliability according to the DISCERN framework. An average reliability score of 3.5 or lower indicates that, while some

shorts contained partially trustworthy information, they generally lacked critical elements such as clear citation of sources, discussion of risks alongside benefits, or acknowledgment of uncertainties in treatment options.

Moreover, since majority of shorts fell below the threshold, this suggests that viewers are often exposed to incomplete, potentially biased, or oversimplified guidance about nutrition. Thus, these scores highlight that most shorts are insufficient for supporting informed decision-making. For teens or individuals with limited health literacy, this may lead to overreliance on simplified advice without understanding limitations, risks, or evidence-based alternatives. As a result, it directly impacts its usefulness as health guidance.

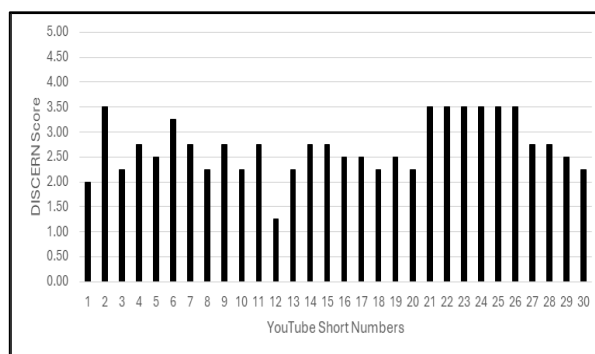


**Figure 7 Overall Average Reliability Score of Nutrition Related YouTube Shorts**

Figure 8 presents the average reliability score for each of the DISCERN reliability questions. Specifically, the shorts reliability score for providing sources, update resources, support, and areas of uncertainty scored poorly with an average DISCERN scores below 1.60.

These results suggest that while some shorts may present nutrition-related claims, they rarely provide the supporting evidence necessary for viewers to verify accuracy or credibility. The particularly low scores in areas such as providing sources, offering updated resources, and acknowledging uncertainties highlight a systemic weakness that the content tends to present information as definitive rather than contextualized.

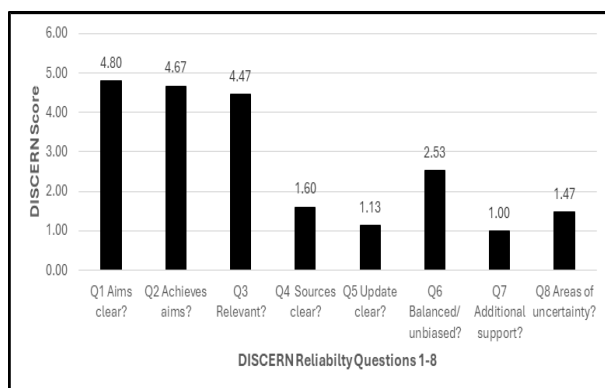


**Figure 8 Average Reliability Score for each of the DISCERN Reliability Questions 1-8**

As shown in Figure 9, the overall average quality of information on treatment choice scores tended to be higher than 2.0. Again, the shorts which had an overall quality score of 5 also have the highest overall average reliability scores. Additionally, one other YouTube short (Number 28) had an overall average score of above 3.0. The remaining shorts had an overall average reliability scores less than 3.0.

These results suggest that while some shorts provide moderately useful guidance on treatment choices, very few achieve a level of reliability that would make them trustworthy sources of health information. As a result, those with limited nutritional literacy are likely to encounter incomplete or potentially misleading treatment guidance, which undermines their ability to make informed decisions.

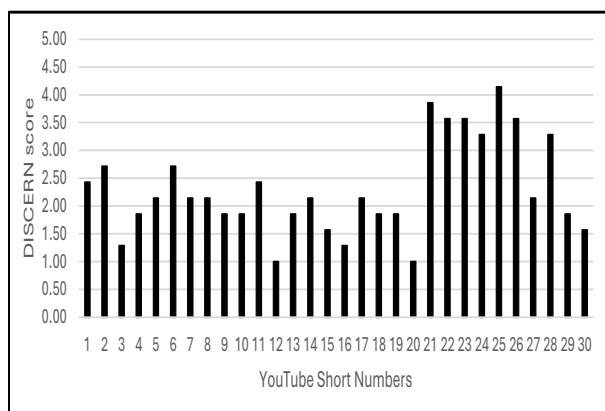


**Figure 9 Overall Average Quality of Information on Treatment Choice for Nutrition Related Shorts**

To further understand additional details regarding Quality of Information on Treatment Choice, figure 10 displays the average score for each of the DISCERN Quality of Information on Treatment Choice questions. Specifically, the

shorts' reliability score for questions 12 (Q12: If advice is not followed), 14 (Q14: More than one approach), and 15 (Q15: Support shared decision making) scored poorly with an average DISCERN scores equal to or below 1.8.

These findings indicate that the content tends to present nutrition advice in a simplified, one-dimensional manner rather than acknowledging the complexity of treatment options and the role of individual choice. As a result, those with limited health literacy may foster an incomplete understanding of nutrition practices, potentially discouraging consultation with professionals or exploration of safer, evidence-based alternatives.

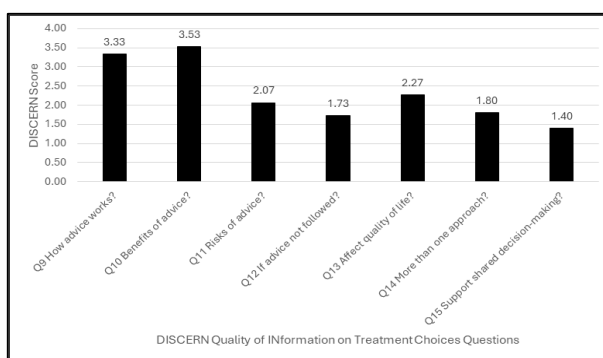


**Figure 10. Average Quality of Information on Treatment Choice Score per Questions 9-15**

## 5. CONCLUSIONS, LIMITATIONS AND NEXT STEPS

As noted by Boté-Vericad (2025), when providing educational content, there is a significant preference for content on YouTube videos to be produced by established and credible individuals or organizations. The results of our study showed that there is an overwhelming number ( $n=2,200$ ) of shorts produced on YouTube over the last two years regarding nutrition, nutritional facts, nutritional values and nutritional food. Among these shorts only 1.36% ( $n=30$ ) were produced by credentialed and authoritative individuals/organizations within the field and were able to be further assessed via a LLM using the DISCERN instrument to assess for quality. Only 6 were identified by a LLM to be DISCERN overall quality. Hence, only 20% of the nutritional shorts achieved a top-quality rating.

Our results are very concerning as for many viewers, especially teens with limited nutritional literacy or restricted access to traditional nutrition advice, these shorts may be a primary

source of information. We believe that our research supports our argument that there is a significant problem regarding the quality of health-related content available on social media platforms like YouTube, particularly in the shorts format for nutritional related content. Moreover, our results are similar to existing social media studies (Boté-Vericad, 2025; Jang et al., 2024) which emphasize the need for future research and policies focusing on the creation and distribution of high-quality educational content.

It is important to note that this research is not without limitations. First, it is limited in scope to specific health related content such as nutrition. Second, it is isolated to specific digital content such as YouTube. Third, several parameters were used which exclude data from being viewed as quality. For example: If the video was not in the English language, then it was excluded. Future research should address these limitations and expand the scope of the topics evaluated in YouTube.

While this research does have limitations, it does offer valuable insights to health professionals, non-profit health organizations, government policy writers and lobbyists, technology educators, as well as researchers looking to evaluate the quality of YouTube shorts. This paper may also be used in a management information system (MIS) course as an applied resource/case for students learning about how to use Google Trends to learn more about searching behaviors, APIs, writing Python code to extract YouTubes based upon criteria, utilizing transcription software, understanding the PRISMA process, and writing good LLM prompts.

We believe through such applications addressed in this paper; students gain exposure to both technical skills and critical thinking about the societal impacts of digital media. Furthermore, embedding these types of learning exercises in an MIS course can bridge the gap between data science methods and real-world implications, while also training future professionals to detect misinformation and evaluate credibility in digital spaces.

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## Appendix A

**Table 3: Python Code for Fetching YouTube Videos with Parameters via a Google API**

```
# First install isodate
pip install isodate

#After installing isodate, run the following code
import requests
from datetime import datetime
# To parse ISO 8601 durations
import isodate
# To export the results to a csv file, you will need to import csv
import csv
# The parameters of searching and pulling the youtube videos via Google API
def search_youtube_videos(api_key, search_queries, max_results_per_keyword=5000, output_csv="youtube_results.csv"):
    search_url = "https://www.googleapis.com/youtube/v3/search"
    video_details_url = "https://www.googleapis.com/youtube/v3/videos"
    start_date = "2023-01-01T00:00:00Z"
    end_date = "2025-01-01T00:00:00Z"
    all_videos = []
    for search_query in search_queries:
        # To exclude ads use '-ad' in the search query
        refined_query = f"{search_query} -ad"
        params = {
            "part": "snippet",
            "q": refined_query,
            "type": "video",
            # To only fetch short videos This is where Anaconda Clouds AI Assistance was used.
            "videoDuration": "short",
            # To fetch only those videos published after defined start date and end date
            "publishedAfter": start_date,
            "publishedBefore": end_date,
            # To fetch only those videos with a prioritize English-language
            "relevanceLanguage": "en",
            "maxResults": max_results_per_keyword,
            "key": api_key)
        next_page_token = None
        while True:
            if next_page_token:
                params["pageToken"] = next_page_token
            response = requests.get(search_url, params=params)
            if response.status_code != 200:
                print(f"Error fetching results for keyword '{search_query}':", response.json())
                break
            data = response.json()
            video_ids = [item["id"] for item in data.get("items", [])]
            if not video_ids:
                break
        # To fetch video details (keywords, video title, channel title, URL, and duration in minutes)
        video_params = {
            "part": "contentDetails,snippet",
            "id": ",".join(video_ids),
            "key": api_key}
        video_response = requests.get(video_details_url, params=video_params)
        if video_response.status_code != 200:
```

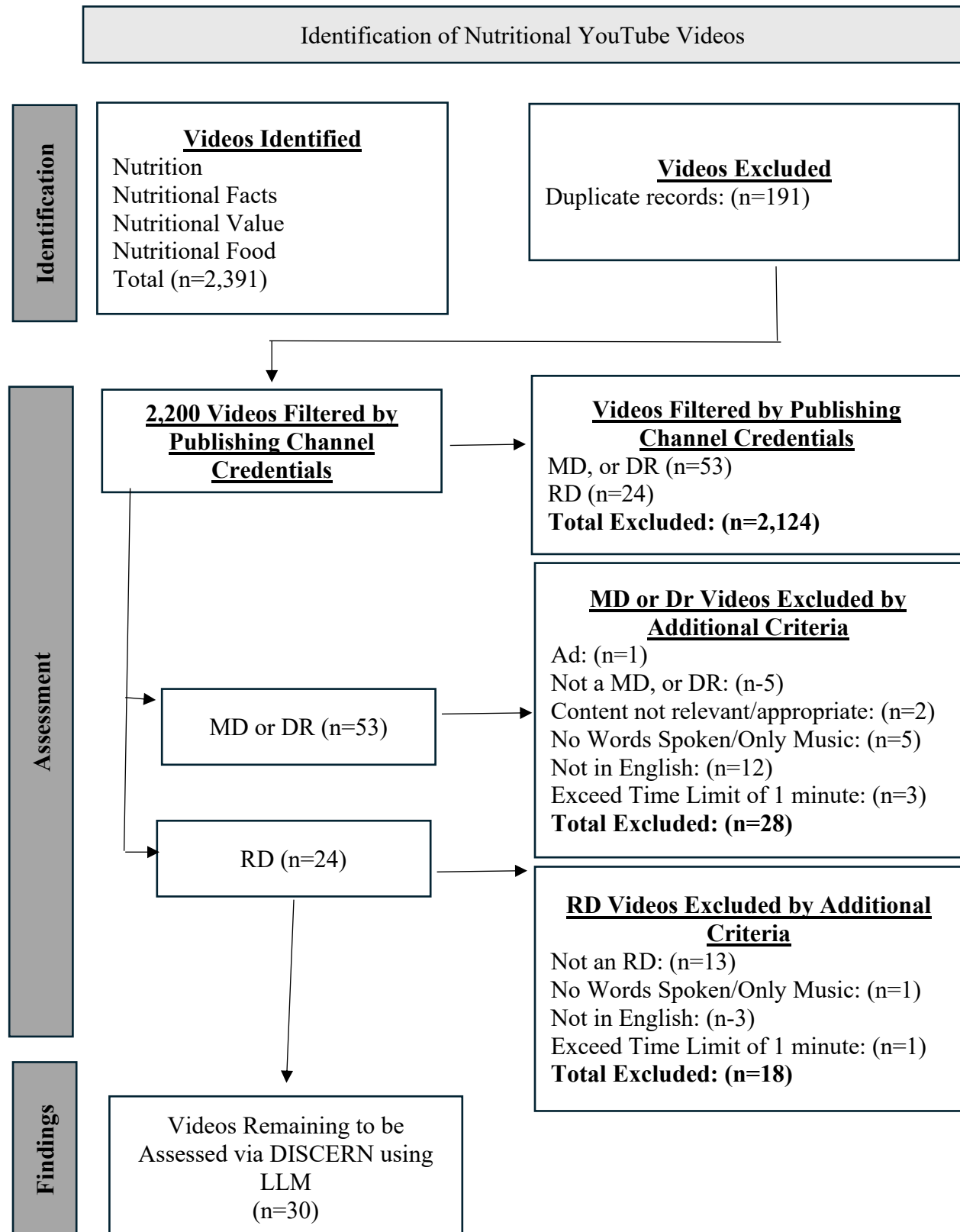
---

```
        print(f"Error fetching video details for '{search_query}':", video_response.json())
        break
    video_data = video_response.json()
    for item in video_data.get("items", []):
        video_id = item["id"]
        title = item["snippet"]["title"]
        channel = item["snippet"]["channelTitle"]
        url = f"https://www.youtube.com/watch?v={video_id}"
        duration = isodate.parse_duration(item["contentDetails"]["duration"])
        duration_in_minutes = f"{int(duration.total_seconds() // 60)}:{int(duration.total_seconds() % 60):02}"
        all_videos.append({"keyword": search_query, "title": title, "channel": channel, "url": url, "duration":
duration_in_minutes})
    next_page_token = data.get("nextPageToken")
    if not next_page_token or len(all_videos) >= max_results_per_keyword:
        break
# To export or write results to CSV file
with open(output_csv, mode="w", newline="", encoding="utf-8") as file:
    writer = csv.DictWriter(file, fieldnames=["keyword", "title", "channel", "url", "duration"])
    writer.writeheader()
    writer.writerows(all_videos)
print(f"Results have been saved to {output_csv}")
# We removed our API Key and replaced it with X's
# Replace the Xs with your API key
api_key = "XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX"
# To fetch videos via our 4 search terms
search_queries = ["Nutrition", "Nutritional Facts", "Nutritional Food", "Nutritional Value"]
# To print the results to an output file titled "my_results.csv"
search_youtube_videos(api_key, search_queries, max_results_per_keyword=5000, output_csv="my_results.csv")
```

---

## Appendix B

### PRISMA flow diagram for video selection process



## Appendix C

**Table 4: Details Regarding the Included Shorts**

| Short | Length | No. of<br>Subscribers | No. of<br>Views | No. of<br>Likes | No. of<br>Comments | Country | Cross<br>Channeled<br>on<br>Instagram<br>or TikTok | Credential        |
|-------|--------|-----------------------|-----------------|-----------------|--------------------|---------|----------------------------------------------------|-------------------|
| 1     | 0.042  | 172,000               | 3,765           | 58              | 33                 | USA     | YES                                                | MD                |
| 2     | 0.041  | 493,000               | 72,327          | 5,200           | 260                | USA     | YES                                                | MD                |
| 3     | 0.024  | 6,460                 | 306             | 7               | 0                  | USA     | YES                                                | MD                |
| 4     | 0.032  | 31,000                | 14,980          | 497             | 3                  | USA     | YES                                                | DR                |
| 5     | 0.041  | 38,600                | 1,613           | 47              | 1                  | India   | YES                                                | DR                |
| 6     | 0.04   | 226                   | 120             | 5               |                    | USA     | NO                                                 | DR                |
| 7     | 0.031  | 24,000                | 149,606         | 3,500           | 66                 | Germany | NO                                                 | DR                |
| 8     | 0.035  | 24,000                | 4,605           | 234             | 5                  | Germany | NO                                                 | DR                |
| 9     | 0.04   | 523,000               | 387,765         | 17000           | 241                | USA     | YES                                                | MD                |
| 10    | 0.04   | 523,000               | 5,921           | 360             | 13                 | USA     | YES                                                | MD                |
| 11    | 0.02   | 523,000               | 17,981          | 858             | 6                  | USA     | YES                                                | MD                |
| 12    | 0.023  | 523,000               | 4,501           | 206             | 1                  | USA     | YES                                                | MD                |
| 13    | 0.013  | 3,530,000             | 419,364         | 15000           | 453                | USA     | NO                                                 | MD (Organization) |
| 14    | 0.017  | 3,530,000             | 384,694         | 16000           | 1006               | USA     | NO                                                 | MD (Organization) |
| 15    | 0.016  | 3,530,000             | 63,545          | 4000            | 306                | USA     | NO                                                 | MD (Organization) |
| 16    | 0.022  | 3,530,000             | 284,899         | 20000           | 563                | USA     | NO                                                 | MD (Organization) |
| 17    | 0.026  | 3,530,000             | 590,522         | 35000           | 831                | USA     | NO                                                 | MD (Organization) |
| 18    | 0.014  | 3,530,000             | 251,959         | 12000           | 362                | USA     | NO                                                 | MD (Organization) |
| 19    | 0.039  | 3,530,000             | 1,072,971       | 66000           | 1543               | USA     | NO                                                 | MD (Organization) |
| 20    | 0.026  | 3,530,000             | 42,851          | 4500            | 230                | USA     | NO                                                 | MD (Organization) |
| 21    | 0.037  | 1,790,000             | 21,388,509      | 1300000         | 4591               | USA     | YES                                                | RD                |
| 22    | 0.039  | 1,790,000             | 6,836,922       | 458000          | 2654               | USA     | YES                                                | RD                |
| 23    | 0.035  | 1,790,000             | 10,917,808      | 614000          | 2651               | USA     | YES                                                | RD                |
| 24    | 0.017  | 1,790,000             | 1,395,474       | 105000          | 348                | USA     | YES                                                | RD                |
| 25    | 0.041  | 1,790,000             | 6,680,914       | 413000          | 2570               | USA     | YES                                                | RD                |
| 26    | 0.028  | 1,790,000             | 1,768,767       | 133000          | 719                | USA     | YES                                                | RD                |
| 27    | 0.032  | 14,100                | 584,720         | 17000           | 125                | USA     | NO                                                 | MD (Organization) |
| 28    | 0.042  | 1,430,000             | 37,943          | 3300            | 81                 | USA     | YES                                                | MD                |
| 29    | 0.026  | 81,600                | 46,781          | 1900            | 72                 | USA     | YES                                                | MD                |
| 30    | 0.019  | 351,000               | 6,687           | 579             | 13                 | USA     | NO                                                 | MD                |

## Appendix D

**Table 5: DISCERN Scores by Short and Question**  
(produced by Gemini 2.5 Flash Preview 05-20)

|           | Reliability |     |     |     |     |     |     |     |                           | Quality of Information on Treatment Choices |      |      |      |      |      |      |                                              | Overall Quality |
|-----------|-------------|-----|-----|-----|-----|-----|-----|-----|---------------------------|---------------------------------------------|------|------|------|------|------|------|----------------------------------------------|-----------------|
| Video No. | Q 1         | Q 2 | Q 3 | Q 4 | Q 5 | Q 6 | Q 7 | Q 8 | Overall Reliability Score | Q 9                                         | Q 10 | Q 11 | Q 12 | Q 13 | Q 14 | Q 15 | Overall Quality of Info on Treatment Choices | Q 16            |
| 1         | 3           | 3   | 5   | 1   | 1   | 1   | 1   | 1   | 2.00                      | 3                                           | 3    | 3    | 3    | 3    | 1    | 1    | 2.43                                         | 1.00            |
| 2         | 5           | 5   | 5   | 3   | 3   | 3   | 1   | 3   | 3.50                      | 3                                           | 3    | 5    | 3    | 1    | 3    | 1    | 2.71                                         | 3.00            |
| 3         | 3           | 3   | 5   | 1   | 1   | 3   | 1   | 1   | 2.25                      | 1                                           | 1    | 1    | 1    | 1    | 3    | 1    | 1.29                                         | 1.00            |
| 4         | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 3                                           | 5    | 1    | 1    | 1    | 1    | 1    | 1.86                                         | 3.00            |
| 5         | 5           | 5   | 3   | 3   | 1   | 1   | 1   | 1   | 2.50                      | 3                                           | 5    | 1    | 1    | 3    | 1    | 1    | 2.14                                         | 1.00            |
| 6         | 5           | 5   | 5   | 3   | 3   | 3   | 1   | 1   | 3.25                      | 3                                           | 3    | 5    | 3    | 1    | 3    | 1    | 2.71                                         | 3.00            |
| 7         | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 5                                           | 3    | 1    | 1    | 3    | 1    | 1    | 2.14                                         | 3.00            |
| 8         | 5           | 3   | 5   | 1   | 1   | 1   | 1   | 1   | 2.25                      | 1                                           | 3    | 3    | 3    | 3    | 1    | 1    | 2.14                                         | 1.00            |
| 9         | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 5                                           | 3    | 1    | 1    | 1    | 1    | 1    | 1.86                                         | 3.00            |
| 10        | 5           | 5   | 3   | 1   | 1   | 1   | 1   | 1   | 2.25                      | 3                                           | 5    | 1    | 1    | 1    | 1    | 1    | 1.86                                         | 1.00            |
| 11        | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 3                                           | 3    | 3    | 3    | 3    | 1    | 1    | 2.43                                         | 3.00            |
| 12        | 3           | 1   | 1   | 1   | 1   | 1   | 1   | 1   | 1.25                      | 1                                           | 1    | 1    | 1    | 1    | 1    | 1    | 1.00                                         | 1.00            |
| 13        | 5           | 5   | 3   | 1   | 1   | 1   | 1   | 1   | 2.25                      | 1                                           | 5    | 1    | 3    | 1    | 1    | 1    | 1.86                                         | 1.00            |
| 14        | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 5                                           | 1    | 3    | 1    | 1    | 3    | 1    | 2.14                                         | 3.00            |
| 15        | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 1                                           | 3    | 1    | 1    | 1    | 3    | 1    | 1.57                                         | 3.00            |
| 16        | 5           | 5   | 5   | 1   | 1   | 1   | 1   | 1   | 2.50                      | 3                                           | 1    | 1    | 1    | 1    | 1    | 1    | 1.29                                         | 1.00            |
| 17        | 5           | 5   | 5   | 1   | 1   | 1   | 1   | 1   | 2.50                      | 3                                           | 5    | 1    | 1    | 3    | 1    | 1    | 2.14                                         | 1.00            |
| 18        | 5           | 5   | 3   | 1   | 1   | 1   | 1   | 1   | 2.25                      | 5                                           | 3    | 1    | 1    | 1    | 1    | 1    | 1.86                                         | 1.00            |
| 19        | 5           | 5   | 5   | 1   | 1   | 1   | 1   | 1   | 2.50                      | 3                                           | 3    | 1    | 3    | 1    | 1    | 1    | 1.86                                         | 1.00            |
| 20        | 5           | 5   | 3   | 1   | 1   | 1   | 1   | 1   | 2.25                      | 1                                           | 1    | 1    | 1    | 1    | 1    | 1    | 1.00                                         | 1.00            |
| 21        | 5           | 5   | 5   | 3   | 1   | 5   | 1   | 3   | 3.50                      | 5                                           | 5    | 3    | 3    | 5    | 3    | 3    | 3.86                                         | 5.00            |
| 22        | 5           | 5   | 5   | 3   | 1   | 5   | 1   | 3   | 3.50                      | 5                                           | 5    | 3    | 1    | 5    | 3    | 3    | 3.57                                         | 5.00            |
| 23        | 5           | 5   | 5   | 3   | 1   | 5   | 1   | 3   | 3.50                      | 5                                           | 5    | 3    | 1    | 5    | 3    | 3    | 3.57                                         | 5.00            |
| 24        | 5           | 5   | 5   | 3   | 1   | 5   | 1   | 3   | 3.50                      | 5                                           | 5    | 3    | 1    | 3    | 3    | 3    | 3.29                                         | 5.00            |
| 25        | 5           | 5   | 5   | 3   | 1   | 5   | 1   | 3   | 3.50                      | 5                                           | 5    | 5    | 5    | 3    | 3    | 3    | 4.14                                         | 5.00            |
| 26        | 5           | 5   | 5   | 3   | 1   | 5   | 1   | 3   | 3.50                      | 5                                           | 5    | 3    | 1    | 5    | 3    | 3    | 3.57                                         | 5.00            |
| 27        | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 3                                           | 5    | 1    | 1    | 3    | 1    | 1    | 2.14                                         | 3.00            |
| 28        | 5           | 5   | 5   | 1   | 1   | 3   | 1   | 1   | 2.75                      | 3                                           | 5    | 3    | 3    | 5    | 3    | 1    | 3.29                                         | 3.00            |
| 29        | 5           | 5   | 5   | 1   | 1   | 1   | 1   | 1   | 2.50                      | 5                                           | 3    | 1    | 1    | 1    | 1    | 1    | 1.86                                         | 1.00            |
| 30        | 5           | 5   | 3   | 1   | 1   | 1   | 1   | 1   | 2.25                      | 3                                           | 3    | 1    | 1    | 1    | 1    | 1    | 1.57                                         | 1.00            |