

Unveiling cognitive qualities: Evaluating popular YouTube videos for physics education

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Highlights

- Evaluated the cognitive instructional quality of popular physics YouTube videos using the Multimedia Principles Rubric (MPR) grounded in multimedia learning principles.
- Showed that video popularity (Video Power Index) is a weak predictor of cognitive quality—high views/likes do not reliably signal strong instructional design.
- Identified that 3–6 minute videos tend to have higher cognitive quality, while longer videos are generally more popular, highlighting a key selection trade-off for educators.

Abstract

YouTube has revolutionized learning by providing access to instructional videos; however, concerns about video quality and instructional effectiveness persist. Despite the popularity of instructional YouTube videos, limited research exists on their cognitive characteristics, particularly in science education. This knowledge gap hampers effective video selection/integration into educational settings. This study aims to identify the association between such videos' cognitive quality and their popularity, as measured by the Video Power Index, along with content and duration. The goal is to provide comparative information and better means to guide educators in video selection. To achieve this, the study proposes using the Multimedia Principles Rubric (MPR) as a filtering tool to assess cognitive quality based on instructional and multimedia content. A multistage cluster sampling method was employed to select the 60 most-viewed YouTube videos from five content areas of physics, considering three ranges of video length and a specific online age. Regression analysis revealed that the mean MPR could be weakly predicted from popularity. Additionally, three-to-six-minute videos demonstrated better cognitive quality, while six-to-twenty-minute videos were more popular. ANOVAs indicated that cognitive quality was significantly dependent on content and video length. The results shed light on the cognitive landscape of such videos, providing insights. Popularity alone is not a good measure of cognitive quality. It is important to assess the cognitive characteristics of instructional science videos. Integrating online videos into courses requires consideration of instructional design principles and cognitive processes. Careful evaluation using the MPR can help select high-quality instructional resources for effective science education.

Article Info: Research Article

Keywords: filtering tool, cognitive, instructional video, video popularity, rubric, YouTube

1. Introduction

Individuals of all ages now rely on the Internet to learn new things, even formally. YouTube, in particular, has had one of the most profound impacts in this trend (Orús et al., 2016; Pires et al., 2022), as the second-most frequently browsed location on the planet in recent years (Ng & Taneja, 2023). YouTube is thought to have revolutionized the approach to learning because it has made information accessible and ever

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available, where a tutor is only a single click away from an interested person and anyone can study about any subject at their own speed (Lee & Lehto, 2013). Educators, not to mention, can utilize YouTube's vast repository of resources to better their courses, especially in more recent times, when online learning has proven to be one of the most effective ways to keep the educational system moving forward. YouTube has the potential to be the network that fundamentally changes science education, but only if the mechanisms of how people think and learn are addressed when developing instructional videos, which is where the science of learning and instructional technology would play their roles (Muller, 2014).

From an educational standpoint, and following on from Merrill's (2008) discussion of the effectiveness of web resources, while YouTube's ability to allow users to easily create and share their own content has contributed to YouTube's popularity and success as an instructional medium, it has also reduced instructional efficacy, making learning from YouTube less productive. A broader range of subjects are covered by YouTube and the Internet in general on a daily basis, but the quality is a growing concern (Frick, 2020). Even videos created to be medically informative are of poor quality (Martinez et al., 2023). A main issue, which has not been as serious earlier, is choosing the right video, which is through content filtering. To ensure that what visitors get is useful to them, filtering is a must. Different methods of filtering exist. Some of the first standards that spring to mind are quality, accuracy, and popularity. However, these standards do not take into account pedagogical and instructional design principles crucial for learning, which are closely connected to the cognitive processes required for perceiving and assimilating new information (Mayer, 2014). Therefore, it is crucial for educators to carefully review videos they intend to integrate into their courses from possible sources including YouTube to determine how closely the videos conform to certain instructional principles like the principles of the cognitive theory of multimedia learning (CTML) (Mayer, 2014). This is especially true for science resources, as studies with such intention are uncommon although they are vastly needed.

In response to this need, this research concentrates on identifying the cognitive properties of YouTube videos, with instructional science videos specifically targeted as a sample to be examined. It also seeks to identify the associations between the cognitive and certain typical properties of YouTube videos, like their content, duration, and popularity. We believe our research will significantly contribute to how educators can consider videos for education based on this comparative information.

2. Background

Students oftentimes become weary and uninterested in studying science, especially physics, because they cannot completely comprehend the ideas and arithmetic required with physics, which is among the most difficult courses to learn for learners and to teach for instructors (Chandra & Watters, 2012). Classical instructional science strategies have negative influence on students (Schultz et al., 2014). The challenge of teaching physics more effectively has long captured the interest of researchers (see Serway & Kirkpatrick, 1988, for an earlier example). Several scholars began examining the issue from novel and distinct angles in an effort to alter how learners perceive physics. Incorporating audiovisual content into the instructional process is one approach that has demonstrated success in improving instructional objectives (Abdulrahman et al., 2020) and influencing attitudes (Galatsopoulou et al., 2022) in various fields. Videos, in particular, are useful audiovisual tools for education (e.g., Hsin & Cigas, 2013; Kay, 2012; Lloyd & Robertson, 2012; Moore & Smith, 2012; Rackaway, 2012; Stockwell et al., 2015).

It has been shown that student engagement can be greatly increased when instructional YouTube videos are played in the class (Mthembu & Roodt, 2017). Aside from being engaging and interesting, videos help to improve cognitive functions, such as retention and comprehension (Berk, 2009). For instance, using audiovisuals and technologies in science classes has been shown to enhance higher-order thinking abilities, which are needed for acquiring knowledge and problem-solving (Resurreccion, 2014). So, developing or leveraging videos for science instruction can improve education and reduce negative perceptions (Gustafsson, 2013), highlighting the value of studying this subject.

The prime objective of using educational audiovisual materials, such as videos, is to assist students in constructing knowledge from the materials provided to them, which includes creating cognitive

representations from oral and visual sensory data. What remains a challenge, however, is creating instructional videos that answer the question, “What experiences promote the kind of thinking that is required for learning?” (Muller, 2014, 4:44). Videos should be instructionally structured in such a way that students can cognitively process information in a meaningful way; otherwise, their experience will be purely recreational (Berk, 2009; Brame, 2016; Muller, 2014). Many multimedia learning researchers have been motivated by this exact idea to look into what makes a good instructional video. There are several publications on the Internet outlining the qualities that are thought to make a successful instructional video (e.g., Brame, 2016; Ten Hove & Van der Meij, 2015).

To be effective, an instructional video should be as short as possible, use casual language, eliminate extraneous details, be straightforward, and feature a limited number of characters (Berk, 2009). Kay (2014) identified 16 features that worked-example video podcasts should have in an experimental study and organized them into four broad categories: “establishing context, using effective explanations, reducing cognitive load, and engaging students” (p. 23), revealing favorable results on students from videos versus textbooks.

The study of videos and their impact on learners is not a recent concept, nor is the utilization of video-sharing sites like YouTube as a medium for education. Despite the fact that common practices in science education such as flipped classroom and STEM (science, technology, engineering, and mathematics), as well as widespread educational applications like distance education all extensively rely on the inclusion of instructional videos, studies focusing on instructional YouTube videos are uncommon. The majority of research looking at YouTube content target the medical sector (e.g., Yurdaisik, 2020). Many concentrates on content and its reliability or on production style and its effects on viewers (e.g., Shoufan, 2019). There is limited literature on the instructional strategies used in YouTube content. A large percentage of science instructors can handle content as being experts on the topic if they need to judge the scope; however, there may be issues with instructional quality because such tasks necessitate a fundamental understanding of research and theories on learning, cognition, and multimedia integration (Koehler & Mishra, 2009). It is not sufficient to simply incorporate video-like audiovisual materials into lessons; rather, it is necessary to better identify and investigate the instructional techniques they exhibit before doing so (Jian-hua & hong, 2012). For this reason, there is a need for further investigation of cognitive characteristics in instructional videos (Shoufan, 2019; Ten Hove & Van der Meij, 2015).

Multimedia learning studies let us explore the ways videos can be created and enhanced for instructional purposes from a cognitive theory standpoint. Nevertheless, the bulk of such research involves scholars creating their own videos for research and utilizing them solely for that purpose, with the settings, subject matter, and research subjects being monitored without excluding teachers, and the variables being kept under control to the fullest extent achievable. This is regrettably not the situation in the actual life, as learners rely on casual Internet resources like YouTube, where videos are plentiful but not always of good standard, to find anything of interest (Haridakis & Hanson, 2009; Khan, 2017). This reality has received little attention in scientific publications, and few studies have been carried out with this goal in mind. The absence of adequate means of filtration has emerged as a major issue for educational community in terms of safety (Bengfort, 2019) and instructional quality, so providing “the right information, at the right time, in the right place, in the right way, to the right person” (Fischer et al., 2023, p. 12) remains a challenge. The fact that it has been explored in science education even to a lesser extent (Gustafsson, 2013) underlines the significance of investigating such research topics.

The goal of the present study is to close this gap in the existing body of knowledge by evaluating the Multimedia Principles Rubric (MPR) (Taher, 2021), a multimedia filtering instrument that can be employed to track down videos with valuable instructional/multimedia content. MPR can offer opportunities to explore potential relationships between certain key aspects of YouTube videos, including the video power index (VPI), an approximate metric for determining how popular a video is, in relation to their cognitive attributes and may better guide educators. In this respect, answers to the following questions were sought:

According to the MPR, what are the cognitive qualities of a representative sample of publicly available instructional physics videos in comparison to VPI, depending on content areas and video lengths?

How does VPI, a measure of video popularity, relate to the overall cognitive quality of videos as measured by MPR?

3. Methodology

This study was conducted in several steps. Cognitive instructional qualities of selected YouTube videos were determined as mean scores using MPR. Their VPI ratings were also calculated using data from YouTube. MPR and VPI ratings were categorized and examined by content area and video length. Finally, VPI ratings were estimated from the MPR scores. Details are provided in the sections below.

3.1. Research Design

The research design of this study employed a quantitative approach, with a descriptive analysis conducted to investigate the videos' content, length, cognitive levels, MPR items, and the video power index (VPI). The metrics on YouTube (views, likes, dislikes, and time online) are used to calculate VPI.

3.2. Sample

A multistage cluster sampling method was used to select 60 most viewed YouTube videos from within five different content areas of physics, with three different ranges of video length, and within a specific online age. This sampling method is thought to be the most appropriate in covering a wide range of physics subjects and durations. Many studies that use the same technique in determining sample videos exist in the literature, particularly in the medical field (e.g., Barlas et al., 2023; Kunze et al., 2019; Yurdaisik, 2020). Our study had two clusters: content area (physics) and video length.

For the first cluster, to determine the content areas that would be representative of physics content in general, four subject matter experts were consulted, whose specialty was physics. The following content areas were recommended by them: (1) Atomic physics, (2) electromagnetism, (3) mechanics, (4) optics, and (5) thermodynamics. The following specific subjects corresponding to the areas were used as *keywords* to search for videos on YouTube in an incognito window, respectively: (1) Bohr's atomic model, (2) Faraday's law, (3) Newton's laws of motion, (4) laws of reflection and refraction, and (5) laws of thermodynamics.

For the second cluster (a subcluster under the first one), we classified the videos into three based on TechSmith's guidelines on how to prepare instructional videos (Knott, n.d.): short (under 3 minutes), medium (equal to or longer than 3 and shorter than 6 minutes), and long (equal to or longer than 6 and shorter than 20 minutes). Bozarth (2021) from TechSmith also reports other similar length divisions. Berk (2009) gives special importance to instructional videos under 3 minutes. Guidelines can also be found for creating videos for other purposes such as marketing (Fishman, 2023). But we believe categorization on instructional purposes would be more useful based on recent data (Knott, n.d.).

The selection of sample videos was implemented as follows: An incognito window was used to access YouTube's website in order to avoid user-specific videos, as practiced by Ten Hove (2014). After typing a *keyword*, the 'view count' and 'English' options were activated. Then, the resulting videos were filtered depending on time since upload to identify and select the most viewed four videos. This process was repeated for each of the three video lengths in each keyword. Videos of in-class lectures, experiments, documentaries, TV programs, and videos targeting young children were excluded. Videos published earlier than 2010 were also excluded.

3.3. Multimedia Principles Rubric (MPR)

The sample videos were analyzed using MPR (Taher, 2021). MPR is a multimedia evaluation rubric. It has 16 items corresponding to 16 multimedia-related principles of design for videos pioneered by Mayer and his colleagues as part of the CTML, which are I01: coherence, I02: signaling, I03: redundancy, I04: spatial contiguity, I05: temporal contiguity, I06: multimedia, I07: segmenting, I08: pre-training, I09: modality, I10: personalization, I11: voice, I12: image, I13: embodiment, I14: dynamic drawing, I15: gaze guidance, I16: subtitle (the I is short for "item"). MPR uses a 5-point Likert scale with the following options to score

the presence of the traits listed in its items: 1 = “Very Poor”, 2 = “Poor”, 3 = “Fair”, 4 = “Good”, and 5 = “Excellent”. By averaging the results of the 16 items on this rubric, a mean MPR score (M_{MPR}) was calculated for each video in the sample. M_{MPR} was used as an indicator of quality and presence of cognitive features in the videos. We also refer to it as pedagogical or instructional value/quality throughout the paper.

3.4. Video Power Index (VPI)

Video popularity in the context of this study was calculated using Equation (1), which is commonly employed, particularly in the medical field, as a useful measure to evaluate the wide acceptance of YouTube videos by taking into account views count, likes/dislikes and video age (e.g., Barlas et al., 2023; Erdem & Karaca, 2018; Kunze et al., 2019; Kuru & Erken, 2020; Yurdaisik, 2020).

$$VPI = \text{Likes Ratio} \times \text{Views Ratio}/100 \quad (1)$$

where the likes ratio is the number of likes divided by the total number of likes and dislikes, and the views ratio is the views count divided by the total number of days the video was online (video age).

In computing the VPI, 58 of the 60 YouTube videos could be included; two videos (one from “Thermodynamics” and the other from “Optics”) were excluded since the likes, dislikes, and channel subscriptions were hidden.

3.5. Statistical Analysis

Descriptive statistics were used to investigate the sample’s quality in terms of cognitive features. The significance of differences in video cognitive quality was examined using two separate one-way ANOVAs, one with content areas as the independent variable and the other with video lengths as the independent variable. Simple linear regression was conducted to predict VPI from M_{MPR} .

4. Results

MPR ratings of the sample videos ranged from $M=2.05$ to a maximum of $M=4.82$ (Figure 1), lowest belonging to I15, gaze guidance, and highest belonging to I04, spatial contiguity, respectively. To some of the videos, one or more of the principles were not applicable. That is why the numbers (n) vary in the figure. The overall M_{MPR} was 4.06 ($SD=0.5$), which is somewhat close to the maximum score, reflecting not excellent but an overall good cognitive quality of the videos.

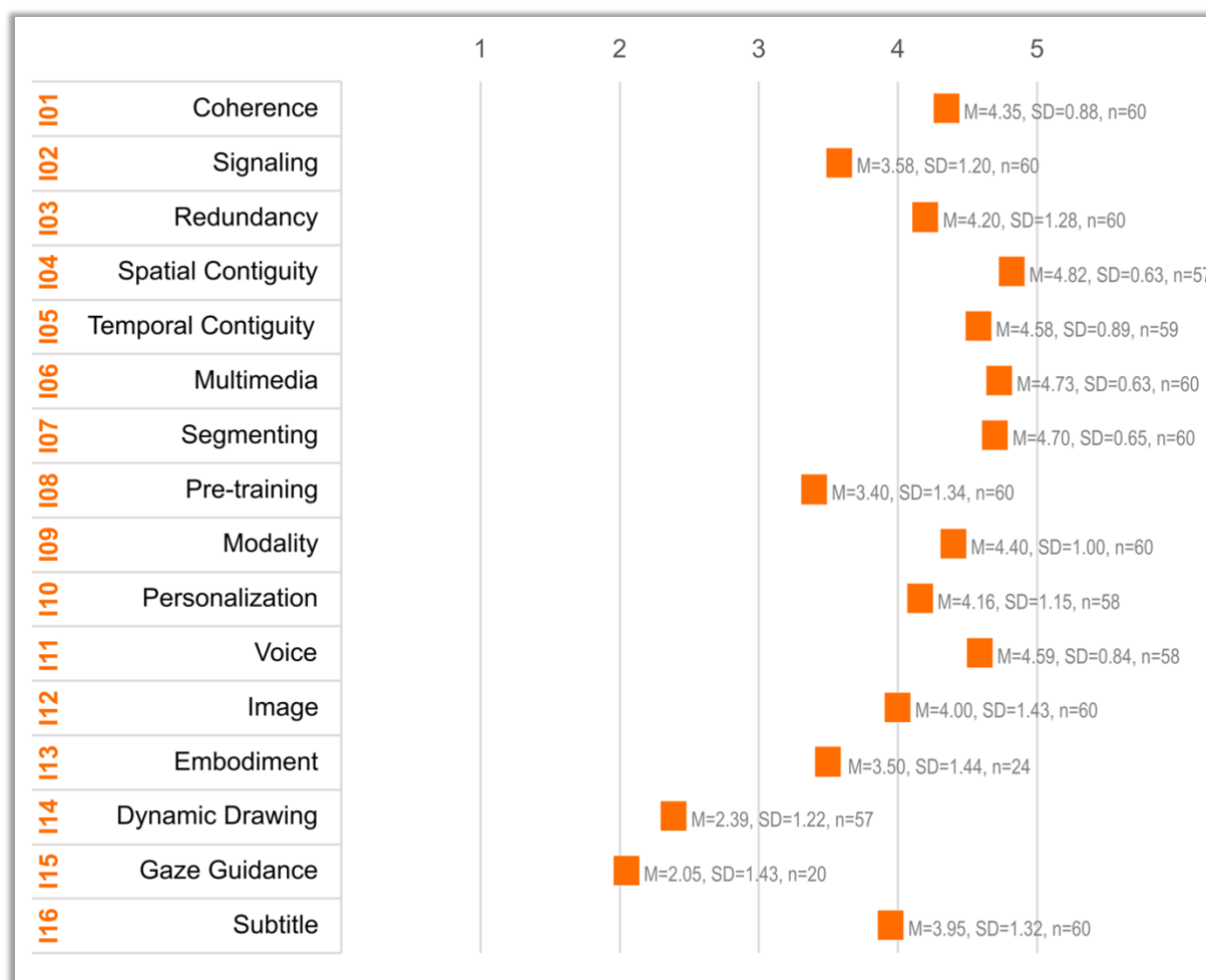


Figure 1. Descriptive characteristics of the sample videos per MPR item (M: mean, SD: standard deviation, n: Observed frequency of the specific MPR item within the sample videos).

4.1. MPR Score and VPI by Content Areas and Video Lengths

Figure 2 illustrates the relationship between M_{MPR} and VPI, as well as the parameters of VPI across the five content areas. To facilitate comparison, the VPI values were scaled down by a factor of 100. As depicted in the figure, there is a noticeable disparity between VPI and M_{MPR} . According to the VPI metric, mechanics videos ranked highest (VPI=493.63) in terms of popularity. Conversely, the M_{MPR} metric indicates that optics videos ($M_{MPR}=4.39$) demonstrated stronger instructional quality compared to other content areas but at the same time they demonstrated the weakest VPI. This stark contrast between VPI and M_{MPR} is evident in their divergent vertical positions on the graph, presenting an intriguing juxtaposition.

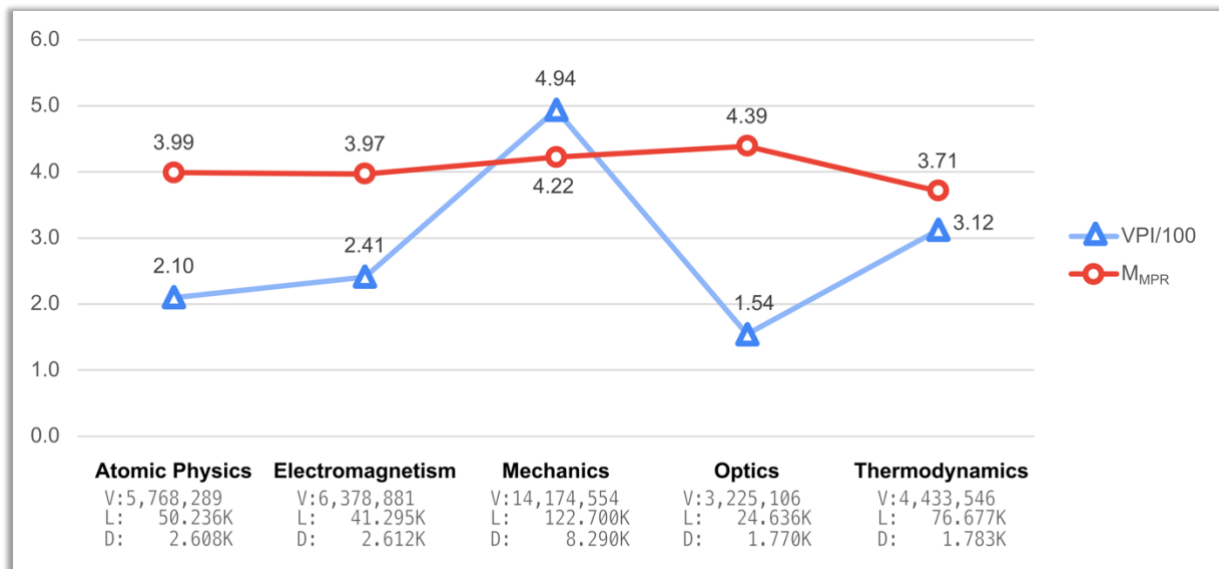


Figure 2. M_{MPR} values in comparison to VPI values depending on content areas. VPI values were divided by 100 to produce visually comparative values. V: views count, L: likes, D: dislikes.

A similar visual comparison between VPI and M_{MPR} was made with respect to video length, as depicted in Figure 3. Like the differences in Figure 2, this examination reveals distinct differences between the two metrics as a function of video length. In particular, as the video length increases, the VPI scores exhibit a nearly exponential growth pattern. In contrast, M_{MPR} scores show an opposite pattern, suggesting that videos of medium length achieve the highest instructional quality ratings. Nevertheless, both metrics concur that shorter videos tend to receive lower quality scores.

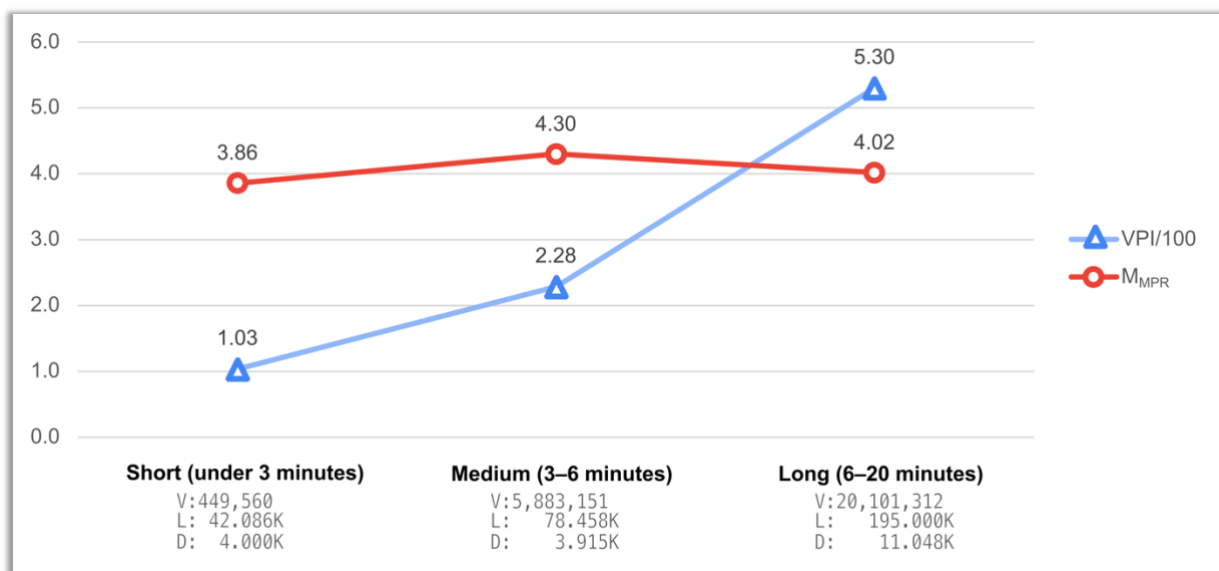


Figure 3. M_{MPR} values in comparison to VPI values depending on video lengths. VPI values were divided by 100 to produce visually comparative values. V: views count, L: likes, D: dislikes.

M_{MPR} scores were further investigated using two separate one-way ANOVAs in terms of content areas and video lengths. M_{MPR} scores were normally distributed [Kolmogorov-Smirnov test: $D(60)=0.074$, $p>0.05$, and Shapiro-Wilk test: $W(60)=0.975$, $p>0.05$], and Levene's F tests of homogeneity of variances yielded non-significant results ($p=0.083$, $p=0.242$, respectively), indicating that the assumptions to conduct ANOVA were met.

The ANOVAs revealed that there was a statistically significant difference in the mean M_{MPR} scores depending on content areas ($F(4,55)=2.932, p=0.029$), as well as video lengths ($F(2,57)=4.726, p=0.013$).

Tukey's honestly significant difference (HSD) test showed that the optics videos ($M_{MPR}=4.39, SD=0.47$) had significantly higher cognitive values than the thermodynamics videos ($M_{MPR}=3.71, SD=0.49$) in terms of M_{MPR} . With regard to video lengths, according to Tukey's honestly significant difference (HSD), the medium-length ($M_{MPR}=4.30, SD=0.46$) videos had significantly higher cognitive quality than the short-length videos ($M_{MPR}=3.86, SD=0.54$).

4.2. MPR Score–VPI Relationship

A major exploration in this study was to show whether M_{MPR} can predict VPI. In other words, it was explored if popularity can be predicted from cognitive value. A simple regression analysis to test this was not viable because the VPI data were not distributed normally [Kolmogorov-Smirnov test: $D(58)=0.21, p<0.05$, and Shapiro-Wilk test: $W(58)=0.73, p<0.05$, both tests showed a significant departure from normality]. For this reason, the raw VPI data were transformed to Ln VPI using natural logarithmic transformation to satisfy the assumptions of normality and linearity needed for regression [$D(58)=0.11, p>0.05$, and $W(58)=0.98, p>0.05$, after transformation] (Ford, 2018). The regression after transformation revealed that a 1-point increase in M_{MPR} results in a 76% increase in the natural logarithm of VPI ($\beta_1=0.76, t=2.624, p=0.011$). Although the association is significant, M_{MPR} explains only 11% of the variance in $\ln VPI$ ($R^2=0.11, F(1,56)=6.887, p<0.05$). The final regression model is given in Equation (2):

$$\ln VPI = 2.032 + 0.757 \times M_{MPR} \quad (2)$$

In order to interpret VPI in its regular unit, the transformed value should be back-transformed. Back-transformation is shown in Equation (3):

$$VPI = e^{(2.032 + 0.757 \times M_{MPR})} \quad (3)$$

5. Discussion

This study looked into the idea that the grounds for a video's popularity may not be proportional to its pedagogical value (Ten Hove & Van der Meij, 2015), with the latter apparently being more crucial for videos to be used for instructional purposes than for videos made and viewed for other purposes, including leisure and entertainment. The relationship between video popularity and cognitive value, however, cannot and should not be disregarded. Accordingly, that is also covered in the current study.

To answer the first research question, the sample videos were first investigated based on individual MPR items (Figure 1). Given that this sample was drawn from among the videos viewed most, it is not unexpected that none of the items received an average rating of very poor. There are interesting results though, at least in terms of two aspects. One is that for some of the videos, one or more of the principles would not apply. This was true especially for gaze guidance (I15) and embodiment (I13). The goal of gaze guidance is for the agent featured in the video to maintain eye contact with the students while occasionally changing the focus to the instructional material found in the video. Embodiment involves an agent acting in the video with human-like gestures and facial expressions. It appears that the majority of the instructional videos sampled do not include the two traits but still make it to the top to be among the most viewed videos. The lack of gaze guidance in the current sample may be because videos of in-class lectures and long videos (>20 minutes) were excluded from the sample, suggesting that gaze guidance appears not to be widely used in videos shorter than 20 minutes. Those two principles deal with an onscreen agent, so the lack of their use as seen in the results might hint to the fact that using an onscreen agent is not common among content

creators of physics videos, this may reflect a tendency in content creators' approaches, with a notable transition from utilizing a human or a human-like presenter to adopting more modern, visually oriented educational videos. Or it might suggest that having an agent might decrease the popularity of a video since the sampled videos were from the most viewed. We recommend further research to explore the reasons for the absence of "Gaze Guidance" (I15) and "Embodiment" (I13).

It should be noted, however, that these results are restricted to the sample examined in this study, which did not include in-class lectures and long videos (>20 minutes). The exclusion of such content was deliberate because, in addition to their long duration, most of these recordings were not initially created for digital educational platforms like YouTube but were repurposed for online dissemination at a later stage. If they had been included, the observed patterns might have been different.

The second aspect is that the sampled videos were of low quality in terms of gaze guidance (I15) and dynamic drawing (I14). Although the majority of the videos did not necessarily involve gaze guidance, as explained, those that did so poorly ($M=2.05$ on a scale of 1 to 5). Similar results were found for dynamic drawing ($M=2.39$). Dynamic drawing entails the lecturer drawing the instructional material while teaching, rather than using a pre-built material. Despite being implemented in 57 out of 60 videos, dynamic drawing was often done not quite satisfactorily. A probable reason can be again the fact that videos of in-class lectures were excluded from the study. In the study of Shoufan (2019), pre-built visuals used by a teacher were more favorable than those drawn by the teacher. In the light of our findings, we speculate that this inclination is not due to dynamic drawing's lack of significance or effectiveness, but rather its poor implementation that seems to negate its value.

The lowest VPI but the highest M_{MPR} were of optics videos (Figure 2). The straightforwardness of the subjects under optics is one of the potential causes of this intriguing discovery. Learners may not have to view several videos to comprehend optics, despite the fact that the creators of the sample optics videos did a great job of including cognitive aspects into the videos, as indicated by the M_{MPR} scores. This notion is supported by the fact that optics has the fewest views, which once more draws attention to the potential effects of the educational content's nature. Another plausible explanation could be that the content itself is perceived as less engaging or boring.

In terms of lengths, the medium-range videos (3–6 minutes) had the highest M_{MPR} but ranked second in popularity as indicated by VPI, followed by the long-range videos (6–20 minutes), which ranked second in M_{MPR} but were the most popular according to YouTube viewers, and unexpectedly, the short-range videos (under 3 minutes) ranked last in both metrics, with the lowest M_{MPR} and VPI values. This may have occurred because content creators often try to cover a lot of material in a brief time, which may result in displaying a lot of text on the screen (violating the redundancy (I03) and signaling (I02) principles) or rapid their speaking (violating the subtitle (I16) principle). This finding contradicts with that of Ten Hove and Van der Meij (2015), who found that popular videos were shorter, in addition to several other studies, such as those of Fishman (2023) and Hsin and Cigas (2013), who reported that shorter videos are generally more engaging and helpful to learners than longer videos. However, it is crucial to think about the learning content and how much time is needed to fully cover it (Berk, 2009), especially for complex or difficult material (Fishman, 2023).

There was a marked contrast between thermodynamics and optics according to M_{MPR} . This may once more be explained by taking into account the characteristics of learning content (Fiorella & Mayer, 2018). Subjects of optics usually involve or urge the lecturer to offer visual materials primarily by penciling them, to signal the key points. This appears to be the reason furthering their M_{MPR} values, as opposed to thermodynamics in which the information does not necessarily involve the lecturer to reinforce it through visual materials, possibly undermining their cognitive values. This means that the need or the way to apply the cognitive principles may have a lot to do with the learning content, some types of content are explained sufficiently by applying a few cognitive principles and ignoring some others, such as topics in thermodynamics. This may explain why, despite its moderate cognitive value, this content area is still favored by viewers (as having the second highest VPI), or simply it might just be a sign that this area of physics is the most difficult for most students requiring them to watch the videos over and over again. In

other words, it seems that the nature of the learning material has an impact on the effectiveness of incorporating some cognitive features (either in the form of benefits or impairments).

Short videos had the lowest M_{MPR} . In order to determine the reason for the discrepancy for short videos, we further studied each MPR item. Even if the scores for dynamic drawing (I14) and gaze guidance (I15) are already low in the sample, the scores for both items in short videos are even worse ($M=2.00$ for both). While these principles are more common and necessary in lengthy lectures, it is understandable that they are absent in shorter videos, as they are time-consuming to produce. This is especially true for dynamic drawing, which requires the creation of visualizations, whereas in short videos, it is faster to use pre-built visual elements. Given all of this information, and the fact that physics subjects in particular require more time and examples to teach, it is clear why long and medium length videos were more popular (high VPI) and rated as more effective instructional materials (high M_{MPR}).

This finding, which compares videos of different lengths, supports the assertion by TechSmith, a prominent video recording and editing software company, that shorter videos are not always more successful (Knott, n.d.). According to TechSmith (Knott, n.d.), 50% of viewers prefer 3–6-minute videos — the same time frame identified as medium length in the present study. In addition, TechSmith's second largest result was for 10–19-minute videos. This range is similar to the long range in the present study and was associated with the highest VPI and second highest M_{MPR} scores. Therefore, these results essentially indicate that most viewers prefer educational videos that are less than 20 minutes in length (Knott, n.d.), with an inclination toward the medium range (3–6 minutes) (Knott, n.d.). This supports the present study's findings in terms of M_{MPR} , but contrasts with it in terms of the popularity ranking of the medium and long ranges. Guo et al. (2014), on the other hand, claimed that short massive open online course (MOOC) videos are more engaging for students. Our findings support TechSmith (Knott, n.d.) and suggest that three minutes or less is a fairly short amount of time to introduce, clarify, and provide examples of scientific concepts or principles.

A regression model with significant contribution should have been expected to predict VPI from M_{MPR} , if the more popular the videos are, the more instructionally valuable they are. However, our findings revealed only a weak relationship that connected the two variables logarithmically. The back-transformed model (Equation (3)) provides some insight into predicting VPI values from M_{MPR} . For instance, for $M_{MPR} = 4.57$, $VPI = e^{2.032} \times e^{(0.757 \times 4.57)} = 240.44$, and the observed VPI was 220.46. Our model explains only 11% of the variance in VPI by M_{MPR} , which is quite small. Although Shoufan's (2019) study uses a multiple regression approach different than the current study (Shoufan's study involves a binary scale to rate the cognitive values of the videos while the current study is using a rubric with a 5-point scale), it may stand as a comparison. Shoufan considered ten cognitive features and relied on their individual contributions, whereas our study takes a wholistic approach, assuming that videos must be successful in terms of all cognitive features (16 in our case) in order to be instructionally sound. When compared to Shoufan's (2019) finding of 63% explained variance, our finding is small. However, this small percentage strongly reinforces our study's main argument: that popularity is a poor indicator of instructional quality. Since 89% of the variance in popularity (represented by VPI) is not explained by cognitive quality (represented by M_{MPR}).

The weak predictive relationship between a video's popularity and its cognitive quality extends beyond a mere statistical observation; it represents a fundamental epistemic challenge in science education in the digital-age, as stated by Allchin (2017) in his analysis of how scientific claims are transmitted and transformed "from test tubes to YouTube". Our finding that popularity is a poor proxy for quality illustrates this disconnect in practice, revealing that learners are at risk of relying on engaging yet insufficient content. This is where MPR can help, as it fosters an active analytical approach to digital resources by empowering users to assess the instructional design of videos critically. It provides a potential means to fill the identified popularity–quality gap, contributing to achieving the greater goal of developing the functional scientific literacy necessary for evaluating scientific claims in personal and public decision-making (Allchin, 2017).

6. Conclusion

Our conclusion is that VPI is not a good indicator of instructional video quality. Educators should not solely rely on common video statistics available on video-sharing sites to make use of videos. The findings reveal a significant divergence: optics videos scored highest in cognitive quality but lowest in popularity, while mechanics videos showed the inverse pattern. The fundamental contrast is further validated by the ANOVA and post-hoc results, which also demonstrate that instructional quality is highly affected by both content area and video duration. Finally, the regression analysis clarifies the nature of this association, indicating that although M_{MPR} is a statistically significant predictor of VPI, it explains only a small portion of its variance (11%). Thus, the collective results from all analyses suggest that a video's popularity on platforms such as YouTube is influenced by factors largely independent of its cognitive instructional value, as defined by multimedia learning principles, which validates the central conclusion of our study.

Furthermore, the findings highlight that the principles of multimedia design were not equally represented in the videos, nor did they equally contribute to the cognitive qualities of the videos, which leave opportunity for growth. Individual MPR item scores indicate shortcomings especially in dynamic drawing and gaze guidance. Both principles deserve stronger attention from content creators. These findings also suggest that although the cognitive quality derived by MPR is not inherently dependent on the presence of a human-like moving element, they indicate that the element's appropriate use significantly enhances a video's cognitive value.

While we used MPR on a small number of specific physics videos, it can be used on any instructional video. In determining instructional potential, MPR identifies as a more accurate evaluation instrument than video popularity (video power index). Nonetheless, even though the sample size of 60 videos is considered sufficient for this study, it yet represents a limited portion and type of the instructional videos available on YouTube, which may pose a limitation on the results' generalizability.

This study showed that MPR is not just about rating videos, but about equipping learners with essential critical skills for the digital world. MPR can also help educators choose finer multimedia content for education that capture learners' attention and maintain their active participation in the learning process, as well as help instructional design specialists, MOOC developers, video creators, and YouTubers develop similar video content.

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