Speculating, Questioning, and Interpreting: A Mixed-Methods Study of Informal Learning on a Video-Sharing Social Media Platform

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Abstract: This study examines how informal learning unfolds on a video-sharing social media platform, focusing on interpretive discourse surrounding explanation videos of a music video. Introducing a mixed methods approach, we integrate computational techniques, including topic modeling, sentiment analysis, and regex-based categorization, with qualitative thematic analysis. This approach enables the examination of a large corpus of comments that would be impractical to analyze manually, carried out across three distinct analytic phases. Our findings reveal that users collaboratively construct meaning through questioning, interpreting, speculating, and debating, engaging in discourse that reflects critical, situated learning practices. These comment sections emerge as dynamic, participatory spaces where cultural interpretation and symbolic analysis are actively negotiated. In addition to these insights, the study presents a scalable, transferable method for analyzing large-scale user-generated discourse in informal, digitally mediated learning environments.

Introduction

Online platforms have transformed informal learning, offering spaces where users engage in critical discussions, co-construct knowledge, and develop new literacies (Dubovi & Tabak, 2020; Lange, 2019; Pires et al., 2022; Tan, 2013). YouTube, as a globally influential social media platform, provides a dynamic space for individuals to engage in discussions that reflect cultural, historical, and narrative understandings, as well as the co-construction of knowledge across temporal and spatial boundaries (Benson, 2015; Lange, 2014; Koehler & Vilarinho-Pereira, 2021). This study explores how informal learning unfolds on a video-sharing social media platform, focusing on interpretive discourse surrounding explanation videos of a music video. We adopt a participation-oriented view of learning (Lave & Wenger, 1991), which conceptualizes learning not merely as the acquisition of knowledge but as a process of becoming through engagement in social, interpretive, and discursive practices. In this view, collaboratively making meaning, posing questions, and articulating speculative claims can be understood as forms of situated informal learning—especially in networked environments where users engage in knowledge-building practices outside formal educational settings. However, analyzing the vast volume and unstructured nature of comment data generated on social media platforms, particularly YouTube, poses significant challenges (Thelwall, 2017). Social media data are not only massive in scale but also multifaceted, with users expressing opinions, sharing experiences, and engaging in discussions on diverse topics. In response, we make two main contributions. First, we present a scalable methodology for analyzing large-scale user-generated YouTube comment data through a combination of computational and qualitative techniques, which can be adapted and applied to various data analysis contexts. Second, by applying this methodology, we demonstrate how YouTube operates as an informal learning environment, enabling users to engage in interpretive discussions through participatory discourse.

Methods

The dataset comprises 3,539 YouTube comments extracted from 12 explanation videos discussing a well-known music video by the group Red Velvet, known for crafting music videos rich with hidden meanings and layered symbolism (Saeji, 2020). Comments were retrieved using the YouTube Data API v3, which provided access to publicly available metadata, including video IDs and comment text. This study proposes a unique mixed methods data analysis framework (Anguera et al., 2018; Creswell & Clark, 2017) that combines computational methods and qualitative analysis, carried out across three distinct phases: (Phase 1) topic modeling and sentiment analysis, (Phase 2) regular expressions (regex)-based automated text analysis, and (Phase 3) qualitative thematic analysis particularly focusing on discussions involving disagreement, agreement, questions, and claims.

In Phase 1, for topic modeling, Latent Dirichlet Allocation (LDA; Blei et al., 2003) was applied to uncover dominant themes within the dataset. Multiple metrics (Arun et al., 2010; Cao et al., 2009; Deveaud et al., 2014) were evaluated to determine the optimal number of topics, resulting in six coherent and interpretable topics. Sentiment analysis was conducted using the Syuzhet and Bing lexicons to identify the emotional tone associated with each topic. In Phase 2, we used regex patterns to classify comments into four categories: agreement, disagreement, questions, and claims. These categories were based on specific linguistic patterns and phrases (e.g., "I agree," "Why does," "I believe") identified in the comments. Comments could belong to multiple categories (e.g., both agreement and question). A concatenated string captured multi-category labels for each comment, allowing detailed frequency analysis and visualization. To validate the regex-based categorization, 300 randomly selected comments were manually coded and compared with the automated results. Precision, recall, and F1-score were calculated for each category, demonstrating strong performance (overall precision: 0.91, recall: 0.87, F1-score: 0.89). In Phase 3, a randomly selected subset of 20 comments from each category (i.e., agreement, disagreement, questions, and claims) was qualitatively analyzed using thematic analysis (Braun & Clarke, 2006) to identify overarching themes and subcategories. Cross-validation of the themes was conducted by the authors, with each independently reviewing the data and resolving discrepancies through discussion.

Results

In Phase 1, six topics were identified in the data. *General reactions* included expressions of excitement, gratitude, and anticipation, often capturing the overall emotional tone of the music and video. *Member-specific discussions* focused on individual singer group members, highlighting their roles and performances. *Lyric interpretation* emerged as another theme, with users analyzing the lyrics and exploring their deeper meanings and broader cultural implications. *Symbolism and theories* were widely discussed, as users speculated about the significance of props, colors, and actions featured. *Emotional and aesthetic responses* centered on the quality of the music, the visual appeal of the videos, and overall aesthetic appreciation. Finally, *storytelling and characters*, focused on the analysis of the narrative elements and character arcs within the video. Sentiment analysis further revealed the emotional undertones of user comments associated with these topics. Showcasing the association between specific words and emotional categories such as joy, anticipation, or surprise, sentiment analysis provided a bird's-eye view of the affective dimensions of user engagement. In Phase 2, comments were categorized into four distinct categories: Agreement (248 occurrences), Disagreement (165 occurrences), Question (1187 occurrences), and Claim (413 occurrences). Question constituted the largest category. Building on insights from the Phase 1 analysis, this suggests that users are engaged in seeking clarification and exploring the video's underlying themes and symbolism. Claim constituted the second most prominent category, reflecting users' speculative interpretations and analytical perspectives. Here, we present the results of Phase 3 with a particular focus on qualitative insights from this Claim category. Analyzing a subset of 20 comments, we identified three primary themes, each illustrating unique ways in which users engage with and interpret the video. *Speculation on Symbolism* was a recurring theme, with users analyzing symbolic elements within videos and attempting to decode the meaning of props, actions, or visual details. Users dissected abstract visual cues, linking them to the broader storyline and speculating about their symbolic roles in driving the plot. Another prominent theme was *Interpretations of Narratives*, where users attempted to uncover the storyline or explore the motivations behind the characters' actions. Users actively constructed narratives, blending their own imagination with perceived elements from the video to make sense of its storyline. Lastly, *Connection to Broader Contexts* emerged as a key theme, reflecting how users linked the video's themes to broader cultural, societal, and historical contexts. Users extended their interpretations to critique the music industry, address broader social dynamics, and contextualize the music video as a cultural artifact reflecting wider societal norms and industry practices.

Scholarly significance of the study

The study demonstrates that users engage in interpretive practices such as symbolic speculation, narrative analysis, and contextual reasoning. These user-generated discussions illustrate how informal learning can emerge organically through everyday digital participation. The high frequency of user-initiated questions in the dataset demonstrates a strong culture of inquiry, where users actively seek clarification, probe deeper meanings, and stimulate further discussion (Garrison et al., 1999). These findings contribute to the understanding of informal learning as a socially situated and participatory process, where user-generated interpretive practices can be seen as forms of knowledge co-construction, even in the absence of formal instruction or structured scaffolding (Gee, 2004; Lave & Wenger, 1991). Our novel analytical approach, and the findings it generated, demonstrate that integrating computational methods—such as sentiment analysis, topic modeling, and regex-based categorization— with qualitative analysis constitutes one approach to understanding large-scale online comment data beyond what either method could achieve independently. The resulting framework is both scalable and transferable, making it applicable to a variety of participatory platforms where user-generated content plays a central role in shaping discourse. Despite the contributions of this study, several limitations warrant attention. The subjective nature of sentiment and interpretation means that some nuance may have been lost in automated processes such as sentiment analysis and regex classification. Future research should explore more robust approaches that combine human expertise with AI techniques to enhance the reliability and interpretive depth of user-generated content analysis.

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