Research on the Influence of Video Content Features on User Behaviour

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Abstract: Research on user engagement behaviours within User-Generated Content (*UGC*) video platforms is notably scarce, despite previous studies predominantly focusing on user-level information. This study contends that enriched video information holds significant value. Its objective is to provide a profound understanding of the influence mechanisms of video content features on user engagement behaviours within *UGC* video platforms. Combining exploratory and quantitative methodologies, the research introduces a highly detailed framework for video content features, covering both cognitive and emotional dimensions. The framework encompasses content richness at the video level and emotional features at the user level. Addressing user behaviours, the study encompasses liking, sharing, saving, and tipping, representing users' varied contributions to the platform. The triggers for user behaviours often originate from diverse motivational intentions. The research focuses on a dual perspective, blending user and video viewpoints when examining video content features. Utilizing linear regression equations grounded in social identity theory and emotional support theory, the study explains the role of video content features in triggering user engagement behaviours. Age and gender serve as moderator variables, exploring behavioural disparities between male and female users and across different age groups. Findings indicate that factors triggering user likes and shares primarily stem from the level of interaction in the comment section, while tipping contributions and video saves are influenced by emotional support during viewing. The study also reveals that sadness enhances user participation intentions, while positive emotions in video characters or commenters diminish user engagement intentions. Lastly, the research adopts web crawling through legally accessible interfaces as the primary data collection method, encompassing 435 videos from 25 food category video authors.

Keywords: User engagement behaviours, Linear regression, Video content features, Social identification theory, Emotional support theory

1. Introduction

1.1 Background

Since the era of the pandemic, with the gradual penetration of the video trend into people's lives, the pan-video market is considered to have enormous development potential. In 2023, the short video platform TikTok surpassed Instagram and Facebook in annual downloads, ranking first globally, with over 1 billion users. However, platforms thriving on the pan-video trend face two major challenges. Firstly, the growth rate of traffic slows down due to the competition for existing users. After the pandemic era, the number of users in the pan-video market tends to saturate, and new user acquisition is slow, especially for platforms focusing on content creation by professional users (*PUGC*). *PUGC* content requires the use of relevant video production tools for arranging and editing videos, demanding higher standards compared to the user-generated content (*UGC*) model of short videos, making it challenging to achieve conversion between users and creators. Attracting more users and transforming them into video creators to enrich the content ecosystem becomes a key strategic focus for platform development. Secondly, enhancing user engagement on social media and cultivating highly sticky users is crucial. In 2023, different types of video platforms have displayed a clear development pattern. The inter-competition among video platforms no longer revolves around capturing user usage duration but shifts towards improving user engagement on social media and cultivating users with high stickiness and a sense of identity. Short video platforms grasp users' fragmented time, enhancing engagement through brand live streaming, video accounts, etc., relying on high user penetration rates. Meanwhile, long video platforms have developed a stable consumer base of highly sticky users, concentrated mainly in popular categories. Addressing the issues of user growth and retention, existing research partly explores the impact of video content on consumers' repurchase intentions through consumer behaviour, identifying key factors that convert casual consumers into highly sticky users. Another portion of research focuses on exploring video reputation and users' psychological experiences to derive various factors that enhance social media engagement. However, fewer studies delve into the exploration of the impact of the physical and emotional dimensions of video content itself on social media engagement, Yan Lin et al (2021) consider the potential for broadcaster sentiment, audience sentiment and audience activity to influence each other, but the goal of the study was limited to tips. Moreover, existing research on user social media engagement analysis often adopts a macro perspective using survey questionnaires, lacking granularity in studying individual videos.

1.2 Definition of Research Topics

With the thriving development of social media platforms, Yoshinobu T et al (1993) and Alan H et al (2005) have pointed out that in the Z era, video platforms integrate features of traditional social media and entertainment platforms, demonstrating the ambiguity and multidimensionality of user engagement. Therefore, social media engagement is widely used to explain various aspects of user psychological and behavioural motivations. Jenny Van D et al (2010) demonstrated that user social media engagement can have profound impacts on platforms, such as loyalty, satisfaction, and commitment. Hence, scholars and industry have paid extensive attention to monitoring, measuring, and explaining user social media engagement. Scholars have proposed various concepts and indicators. The definition of social media engagement varies significantly under different concepts due to the diverse nature of the engaging entities. Some scholars, such as Laurence D et al (2016), believe it can be categorized into customer engagement, brand engagement, and online engagement based on the distinction of engaging entities. Another group of scholars categorizes it into behavioural, emotional, and cognitive dimensions based on engagement dimensions. Therefore, there is still no unified definition of social media engagement, but the academic community generally agrees that the engaging entities are individuals or consumers.

1.3 Research Question and Structure

Building upon the preceding discussion, subsequent research questions have been posed: Do different video content features encourage or inhibit users' willingness to engage in actions such as liking, tipping, saving, and sharing? Furthermore, is the motivation behind these actions dominated by social identity theory or emotional support theory? Therefore, this study will be divided into three sub-questions.

Firstly, what is the impact of cognitive features in videos on user behaviours, and what theoretical underpinning governs the influence of rich details about characters and scenes on motivational factors?

Next, what differences exist in the impact of interactive features in the comment section and bullet screen area on user behaviours, and what motivational theories drive user engagement in interactions?

Lastly, what is the role of emotional features in influencing user behaviours, and are there differences in the impact of character emotions in videos compared to emotional expressions in the user comment section?

In the next chapter, a literature review will evaluate the theories employed in this study and previous research on video content features. Following this, the methods and results employed in this study will be presented. Finally, a summary will conclude the research.

2. State of Research

2.1 User Behaviour Motivation

Theories commonly used to explain user behavioural motivations on social media include Social identity theory and Emotional support theory. Social identity theory, a psychological perspective on motivation and behaviour, refers to an individual perceiving themselves as a member of a group, involving cognitive, emotional, and evaluative components (Dominic A et al, 2006). Cognitive identity reflects the overlap between an individual's self-image and perceived images of others in the group, emotional identity expresses the individual's sense of belonging to the group, and evaluative identity is the individual's perception of their importance within the group. Shih-Chih C et al (2019) highlighted that users in social communities categorize others based on their classification in the online community, either belonging to the same group or another. Limited research exists on the behavioural motivations of social media users (such as liking, tipping and sharing) under the Social identity theory, with most focusing on knowledge sharing and seeking in online communities. Scholars have analyzed the characteristics of the Douyin short video community and its impact on users' intentions for continuous contribution, finding a significant positive correlation between community identity and users' intentions for continuous contribution in *UGC* short video communities. The second theory, Emotional support theory, is a common type of social support closely associated with emotional needs (Ariel S et al, 2020). Users lacking emotional support in the real world often seek it on social media, increasing their willingness to participate (Julia B et al, 2019). Xiaoyu X et al (2019) pointed out that emotional support simultaneously affects users' hedonism, enhances their social presence, motivates them to watch live broadcasts, become loyal fans of the broadcaster, and subsequently engage in consumption behaviour. Additionally, some scholars have found that emotional support enhances viewers' social presence to a certain extent (Donghee Yvette W et al, 2018). However, frequent information interaction weakens this effect of emotional support (Jiada C et al, 2022). Jooyoung L et al (2023) suggested that compared to seeking informational support, supporters of emotional support reveal more self-information, corresponding to fewer comments. Sanghyun K et al (2013) proposed that people can influence and convey emotions to each other through language, behaviour, facial expressions, etc. Thus, in a live-streaming context, the emotions of the host may have a contagious effect, affecting users' cognition and behaviours.

2.2 Video Content Characteristics

Video content characteristics can be classified into cognitive and emotional dimensions. Cognitive features, related to the lower-level physical aspects of video content, are extracted through video summarization, where most state-of-the-art methods focus on analyzing static frames to generate descriptive summaries. Analysis of frames at different scales can extract various essential features, such as different time sliders and sketch representations (HongAn W et al, 2013). Color, a simple yet effective cognitive feature, is commonly used in research on the impact mechanisms of video content on user social media engagement. Besides the widely used RGB components, other cognitive features include hue, saturation, and brightness (Yilin W et al, 2021). Scholars have also studied *UGC* type videos, with Yilin W and colleagues pointing out that the quality of *UGC* videos is determined by CP, CT, and DT (video compression, video content, video distortion). They established a model called TippingVQ to evaluate CT scores by building multippingle granularity content tags and video features. Cognitive features used in TippingVQ include video content (evaluated using tags at various granularity levels), video distortion, compression levels during video uploading, and the average frame quality (William H et al, 2021). In a study on the impact of YouTube videos on user engagement, the contrast of video thumbnails and cognitive features of video categories were found to be the most significant factors influencing video popularity (Shan L et al, 2023). Regarding emotional features, Alan H et al (2005) explored content analysis on the emotional aspects of videos. They used Russell and Mehrabian's definition of emotion, which involves the expected intensity or type of emotion users anticipate while watching a video (James A R et al, 1977). Russell and Mehrabian identified three fundamental dimensions of video emotion: Valence, Arousal, and Control. Valence represents the continuum of emotional states from positive emotions like pleasure and excitement to negative emotions like anger and frustration. Arousal indicates the intensity of Valence, while Control is used to differentiate highly similar valences, such as excitement and happiness. Finally, Shan Lu et al (2023) proposed a variable screening method for component response regression, using deep learning to extract features from multi-modal data of short videos.

3. Methodology

This study conducted a regression analysis of user engagement behaviours on social media platforms based on the user motivation theories outlined above (Figure 1). The data were collected from *Bilibili*, a Chinese social media platform, focusing on videos from creators with over one hundred thousand followers to ensure rich information on user engagement behaviour. Videos were selected from non-holiday periods to exclude the influence of external factors such as seasons. Each individual video was taken as the unit of analysis, and a five-layer high-granularity video content feature framework was constructed for the original videos. This framework included features from both user and video perspectives, incorporating interactive and emotional features. The study integrated and innovatively expanded existing research methods. To measure text sentiment accurately, a personally improved dictionary for network language was employed. Additionally, deep learning techniques were utilized to extract character details and emotional features. From the perspectives of age and gender, moderator variables were introduced, and regression equations were developed for the four user behaviours: liking, tipping, sharing, and saving. The explanatory variables in the regression equation were derived from cognitive and emotional features, with a separation of interactive features (Figure 2).

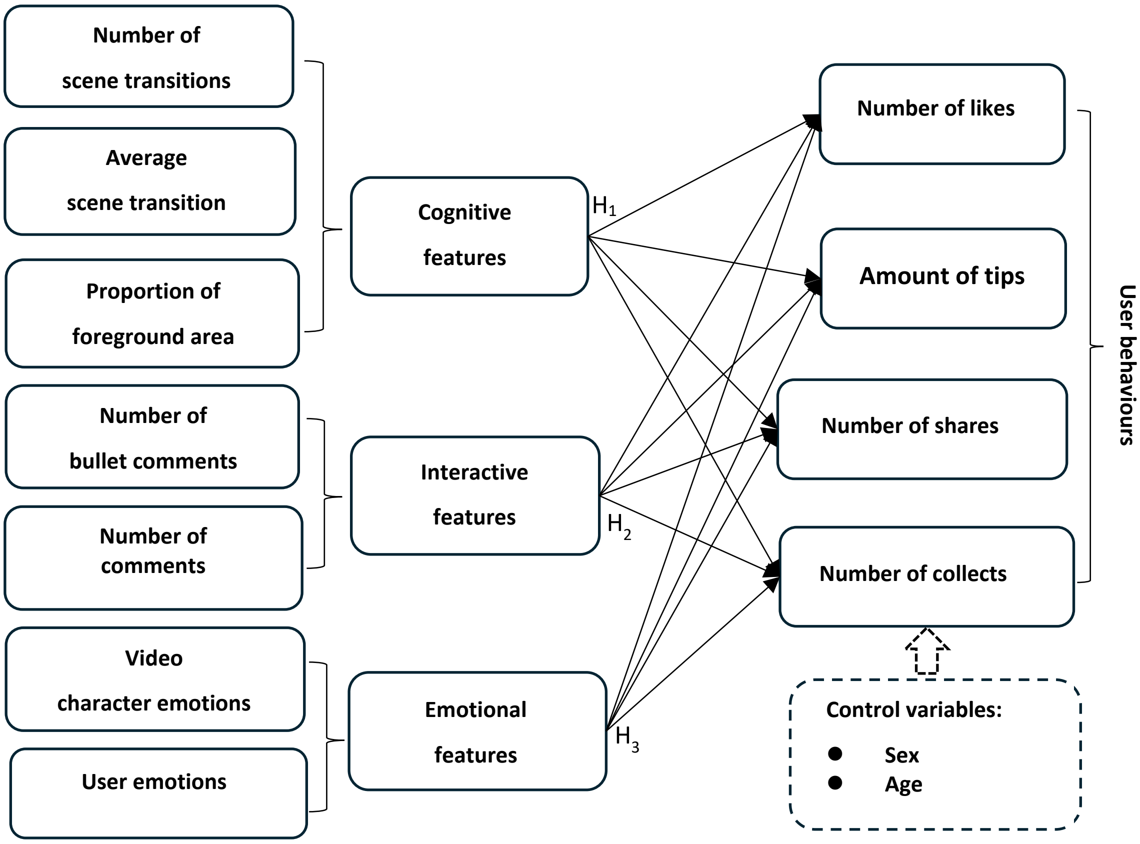

Figure 1: Framework of user behaviours regression equation

Specifically, the interaction features were represented by the number of comments in the comment section and the quantity of bullet comments in the bullet comments section. The comment count not only tallied the headline comments under each subtopic but also calculated collapsed comments across all topics. To extract emotional features from user comments, individual video comments and bullet comments *JSON* files were extracted and integrated into a *TXT* file for analysis. In preprocessing, short texts with fewer than 10 characters in a single line were removed. Subsequently, excessive spaces, consecutive punctuation, and special symbols like emoticons were eliminated. Segmentation was achieved using the CWN Chinese thesaurus and a synonym table based on popular Chinese internet terms. The processed text was then evaluated for sentiment using a pre-labeled sentiment lexicon. For the emotional expressions of characters in the video, *PySceneDetect* was employed to isolate keyframes. These keyframes were transformed into high-dimensional vectors, which were then input into the *FER* model to extract facial expressions of individuals in the video. Simultaneously, Fairface was used to determine the age and gender of individuals in the keyframes.

Video content feature framework			
User behaviour variables			Number of likes, saves, tips, shares
Interactive feature variable			Number of bullet comments, comments
Cognitive variables	video richness		Number of scene transitions
	video detail		Average scene transition time
	video attraction		Foreground area proportion, Character proportion duration
	video visual experience		Hue, Brightness, Contrast
Emotional variables	video character emotions		Neutral, Happy, Sad, Angry
	user emotions	general	Positive emotions of the user, Negative emotions of the user
		single	Single positive emotion, Single negative emotion
Moderator			Gender, age

Figure 2: Video content feature framework in Bilibili context

4. Results

4.1 User Behaviours Dimension Classification

As explained in the preceding chapters, this study employed regression equations to identify significant video content feature variables influencing four user behaviours, summarizing motivational intentions under different user behaviours. Firstly, the research results revealed that the four user behaviours could be categorized into two dimensions based on Social identity theory and Emotional support theory. Liking and sharing were primarily driven by social identification, considering users watching videos as a group with similar interests across different times and spaces. This enhanced user integration into video interactions and fostered a sense of social identity. Accordingly, users are inclined to like and share videos that aligned with their interests or represented their community viewpoints, reinforcing their self-identity based on social identity theory. Simultaneously, the behaviours of tipping and saving were mainly driven by emotionally supporting. Tipping and saving more reflected users' emotional support for video content. The emotional support theory posits that users seek content that satisfies their emotional needs in videos. Once these needs are met, emotional support triggers specific user behaviours. Tipping, as a "substantial" contribution, is primarily influenced by this theory. Users invest their limited virtual tipping, signifying their acknowledgment of the emotional value provided by the video content. The results for saving indicate that the motivation to save is primarily derived from emotional support. Triggering saving behaviour requires a higher level of emotional support from the video compared to tipping.

4.2 Hypothetical Test

In the subsequent paragraphs, this study summarizes key findings regarding the research questions posed earlier (Figure 3). In terms of cognitive features, scene transition frequency has the most pronounced promoting effect on user tipping behaviour. This suggests that a richer variety of scenes in videos gains user approval, thus encouraging tipping rewards. Similarly, cognitive feature variables that have a promoting effect on giving tips include foreground area ratio and average scene transition time. According to the attention focus hypothesis in visual attractiveness theory, a larger area ratio of the foreground area and sufficient dwell time in individual scenes help users concentrate their attention on specific visual elements, ignoring other irrelevant elements, referred to as "visual attractors." Correspondingly, variables that have an inhibitory effect on user tipping include brightness, saturation, video duration, and the proportion of time characters are off-screen. An increase in brightness or saturation leads to color distortion, gradually reducing the user's viewing experience and inhibiting tipping behaviour. The increase in video duration slightly weakens user attention, affecting tipping behaviour. Users also tend to focus their attention on food or the cooking process rather than the characters in the video, validating the promoting effect of the foreground area ratio observed in the previous variables. Simultaneously, variables that have a promoting effect on user liking include brightness and scene transition frequency. However, the impact of scene transitions on promoting liking is relatively limited. The study suggests that rapid changes in scene frequency may shift user attention to the comments or bullet chat area, indirectly affecting liking behaviour. This characteristic is also reflected in the brightness variable; excessive brightness can similarly shift user attention to the comments and bullet comment areas, indirectly promoting liking. Variables that have an inhibitory effect on user liking include video duration, foreground area ratio, proportion of time characters are off-screen, and saturation in video physical features. The study argues that excessively long videos and characters being off-screen for too long reduce user willingness to watch and focus, thus inhibiting liking behaviour. When the foreground area ratio is larger, users focus more on the video content itself than on the comments, weakening their willingness to like. At a higher level, concerning saving and sharing, video duration significantly inhibits saving behaviour. Based on this, the study suggests that not only the content presented in the video but also the way it is presented influences user behaviours. Excessively long videos seem to divert user attention since social identity-based liking behaviour is also inhibited, indicating that longer video duration decreases the overall attractiveness of the video to users. This leads to users ending their viewing or participation earlier, resulting in an overall decrease in willingness. This decrease is reflected in saving, where the emotional support effect generated by the video content is diminished. For sharing, only the hue in physical features has a weak inhibitory effect on sharing, while other cognitive feature variables have no significant impact on it.

Subsequently, the research results regarding interactive features indicate that the interaction level in the comments section and bullet comment area significantly and positively promotes user liking and tipping at a lower level. On one hand, this suggests that intense interaction in the comments and bullet comment areas among users in a shared viewing context directly enhances individual identification with the group, triggering liking behaviour. On the other hand, users derive emotional support from posting and replying to comments, especially when their comments receive numerous likes and replies, leading to emotional satisfaction and subsequently triggering tipping behaviour. When the dependent variable is the number of saves, the results show that the quantity of bullet chat messages in the video remains a key factor in users generating emotional support. The number of bullet comment messages largely determines the intensity of emotional support, thereby promoting user saving or tipping. Simultaneously, the regression results indicate that the number of comments, as a key factor expressing a sense of identification among users, has a certain impact on tipping but no influence on saving. This suggests that the motivation for saving is more dominated by emotional aspects compared to the motivation for tipping, and it is less connected to the sense of identification formed among user groups. When the dependent variable is the number of shares, the number of comments is a key factor influencing user sharing behaviour, while the quantity of bullet comments does not significantly affect sharing behaviour. This indicates that the quantity of bullet comments and the number of comments have different degrees of social identity effects simultaneously.

Continuing with the research results on emotional features, at the level of tipping and liking, users demonstrate emotional support for sad emotions of video characters, thereby promoting tipping behaviour. However, an increase in angry emotions in video characters reduces users' emotional support and inhibits tipping. At the same time, as the number of positive comments increases, users' willingness to liking and tipping decreases. According to the Social identity theory, this study suggests that when users see that most comments are positive, they may feel a certain social identity pressure. This pressure comes from a desire to fit into the group or avoid conflicting with mainstream opinions. In such situations, users may reduce their willingness to like and giving tips to avoid too much inconsistency with other users and maintain social identity.

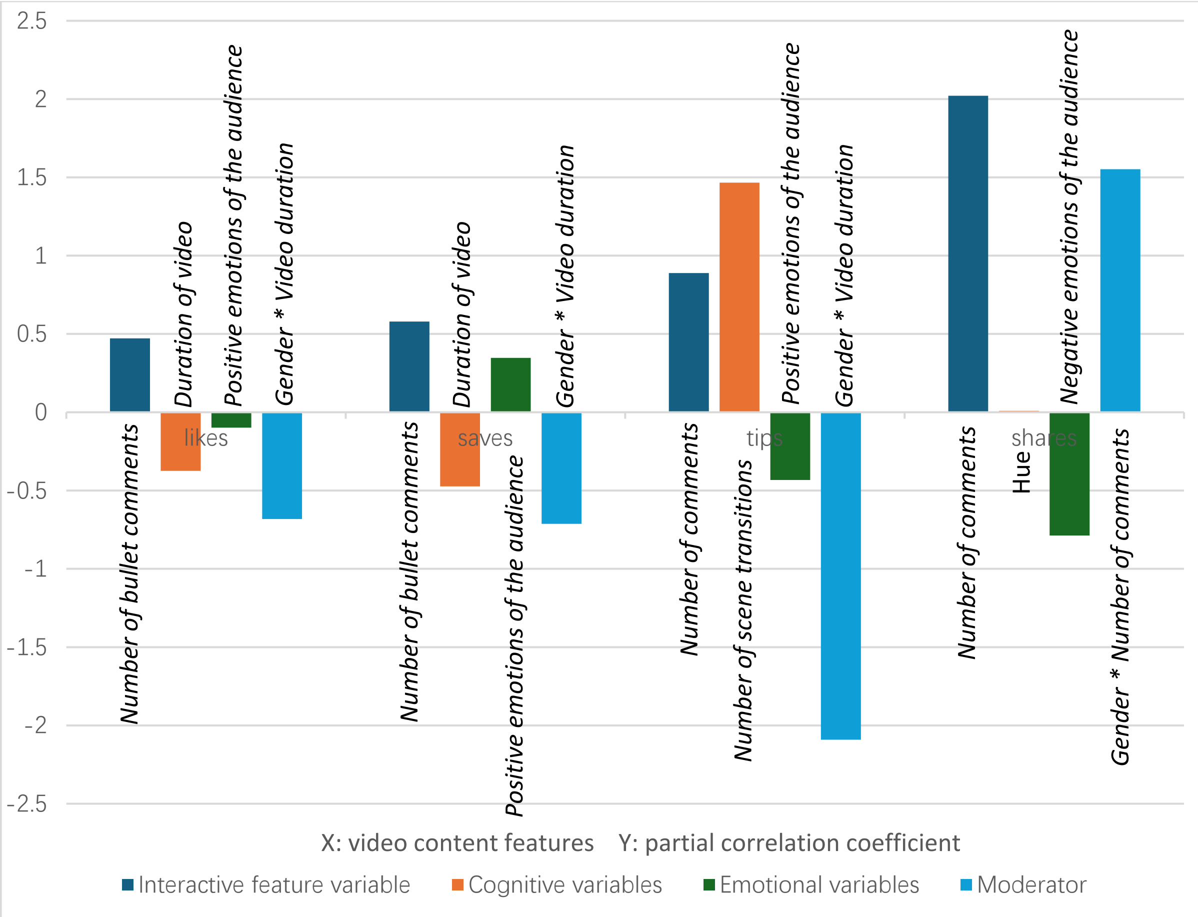

Figure 3: Regression results of video content features on user behaviours

At the level of saving and sharing, this study found opposite effects of angry emotion ratio and user positive emotion ratio in the emotional variables on user tipping and saving. More appearances of angry emotions in video characters and positive emotions in user comments inhibit users tipping. Conversely, these two emotions promote users' willingness to save. Furthermore, users' saving behaviour is influenced by a single negative emotion in the comments, meaning that when there are strongly expressed emotional comments in the comments section, users are more inclined to save the video.

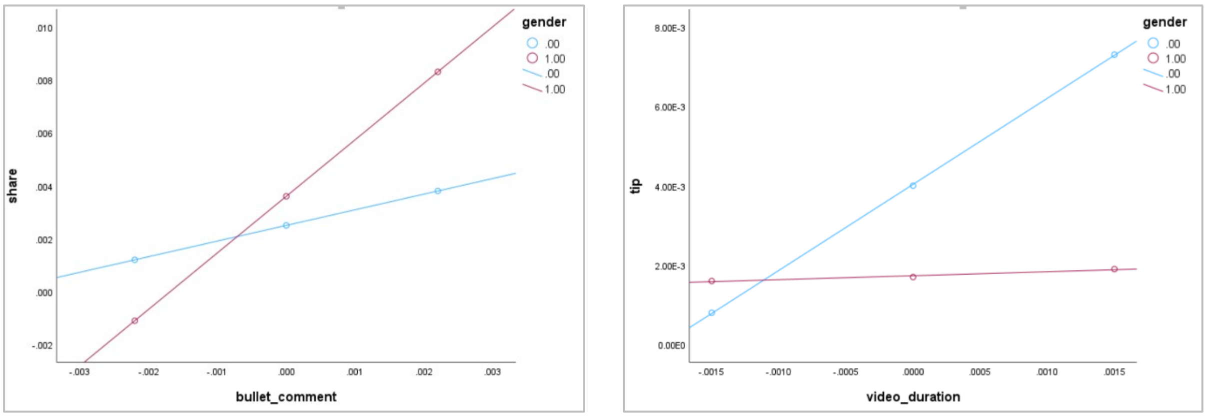

Figure 4: Effect of moderating variable (gender) on sharing and tipping

In the context of moderator variables, the study's findings indicate a significant moderating effect of gender in the influence of video duration on user behaviours. When the user transitions from male to female, the willingness to refrain from actions such as tipping, saving, and liking weakens with the increasing video duration, with tipping showing the most significant decline. Simultaneously, gender's moderating effect on user sharing behaviour is notably pronounced. Female users, in comparison to their male counterparts, tend to favor saving videos as the level of interaction in the video's comment section increases. Furthermore, the study observes that women are more inclined to discontinue liking and tipping as the number of scene transitions in the video rises, with the magnitude of this difference gradually diminishing with an increase in the frequency of scene transitions (Figure 4). Regarding age, older users exhibit a decreasing willingness to like and saving videos as the number of comments and bullet comments increases. This impact tends to diminish with a higher accumulation of comments and bullet comments.

5. Conclusion

In the context of *UGC* videos, this study identifies distinct influencing factors and motivational intentions for user engagement behaviours such as liking, tipping, saving, and sharing. Notably, a rich variety of scene transitions emerges as a primary factor driving users to contribute tips, indicating a preference for emotionally supportive and content-acknowledging scenarios. Additionally, the level of interaction in the video's comment section stimulates tipping behaviour to some extent. Significantly, the study reveals that videos evoking sadness emotions positively influence tipping, while extreme brightness or color distortion during production inhibits tipping. Inaugurally, it's observed that an increase in positive emotional comments in the comment section correlates with a decrease in users' willingness to tip, with negative comments showing no significant impact. In terms of gender and age, female users are more likely to refrain from tipping as video duration increases, and older users may abandon tipping with excessive scene transitions or excessive interaction in the comment section. Social identity emerges as a primary motivational factor for liking behaviour, with the bullet comment section being the strongest contributor, followed closely by the regular comment section. Cognitive factors such as scene transition frequency have a minimal impact on users' tipping intentions. Similarly, extreme brightness, color distortion, and an increase in foreground area proportion inhibit liking behaviour. Emotionally, an increase in the number of positive comments in the comment section suppresses users' willingness to like. In the context of gender and age, female users are more inclined to like as video duration increases, while older users tend to abandon liking with prolonged video duration. Saving and sharing, representing deeper dimensions of user behaviours, show nuanced differences. Saving behaviour primarily stems from emotional support, an extension of tipping behaviour. Sharing behaviour, on the other hand, is an extension of liking, aiming to expand group identity into individual social circles. Emotionally, anger emotions in videos inhibit tipping but encourage saving. Additionally, higher average negative emotions in the comment section strengthen users' motivation to save video. Finally, in the comparative analysis between sharing and liking, it's observed that bullet comment quantity significantly influences liking but has no impact on sharing. Regarding emotional features, anger in videos and excessively negative emotions in the comment section inhibit sharing behaviour.

References

Abrams, D., & Hogg, M. A. (2006). Social identifications: A social psychology of intergroup relations and group processes. Routledge.

Brailovskaia, J., Rohmann, E., Bierhoff, H.-W., Schillack, H., & Margraf, J. (2019). The relationship between daily stress, social support and Facebook addiction disorder. Psychiatry Research, 276, 167–174.

Chen, J., & Liao, J. (2022). Antecedents of viewers' live streaming watching: A perspective of social presence theory. Frontiers in Psychology, 13, 839629.

Chen, S.-C., & Lin, C.-P. (2019). Understanding the effect of social media marketing activities: The mediation of social identification, perceived value, and satisfaction. Technological Forecasting and Social Change, 140, 22–32.

Kang K, Lu J, Guo L, et al. The dynamic effect of interactivity on customer engagement behavior through tie strength: Evidence from live streaming commerce platforms[J]. International Journal of Information Management, 2021, 56: 102251.

Lin Y, Yao D, Chen X. Happiness begets money: Emotion and engagement in live streaming[J]. Journal of Marketing Research, 2021, 58(3): 417-438.

Lu S, Yu M, Wang H. What matters for short videos' user engagement: A multiblock model with variable screening[J]. Expert Systems with Applications, 2023, 218: 119542.

Dessart, L., Veloutsou, C., & Morgan-Thomas, A. (2016). Capturing consumer engagement: Duality, dimensionality and measurement. Journal of Marketing Management, 32(5-6), 399–426.

Hanjalic, A., & Xu, L.-Q. (2005). Affective video content representation and modeling. IEEE Transactions on Multimedia, 7(1), 143–154.

Hoiles, W., Aprem, A., & Krishnamurthy, V. (2017). Engagement and popularity dynamics of YouTube videos and sensitivity to meta-data. IEEE Transactions on Knowledge and Data Engineering, 29(7), 1426–1437.

Hu, M., Zhang, M., & Wang, Y. (2017). Why do audiences choose to keep watching on live video streaming platforms? An explanation of dual identification framework. Computers in Human Behaviour, 75, 594–606.

Kim, S., & Park, H. (2013). Effects of various characteristics of social commerce (s-commerce) on consumers' trust and trust performance. International Journal of Information Management, 33(2), 318–332.

Lee, J., Rajtmajer, S., Srivatsavaya, E., & Wilson, S. (2023). Online self-disclosure, social support, and user engagement during the COVID-19 pandemic. ACM Transactions on Social Computing, 6(3-4), 1–31.

Lu, S., Yu, M., & Wang, H. (2023). What matters for short videos' user engagement: A multiblock model with variable screening. Expert Systems with Applications, 218, 119542.

Russell, J. A., & Mehrabian, A. (1977). Evidence for a three-factor theory of emotions. Journal of Research in Personality, 11(3), 273–294.

Shensa, A., Sidani, J. E., Escobar-Viera, C. G., Switzer, G. E., Primack, B. A., & Choukas-Bradley, S. (2020). Emotional support from social media and face-to-face relationships: Associations with depression risk among young adults. Journal of Affective Disorders, 260, 38–44.

Tonomura, Y., Akutsu, A., Otsuji, K., & Sadakata, T. (1993). Videomap and videospaceicon: Tools for anatomizing video content. In Proceedings of the INTERACT'93 and CHI'93 Conference on Human Factors in Computing Systems (pp. 131–136).

Van Doorn, J., Lemon, K. N., Mittal, V., Nass, S., Pick, D., Pirner, P., & Verhoef, P. C. (2010). Customer engagement behaviour: Theoretical foundations and research directions. Journal of Service Research, 13(3), 253–266.

Wang, H., & Ma, C. (2013). Interactive multi-scale structures for summarizing video content. Science China Information Sciences, 56, 1–12.

Wang, Y., Ke, J., Talebi, H., Yim, J. G., Birkbeck, N., Adsumilli, B., ... Yang, F. (2021). Rich features for perceptual quality assessment of UGC videos. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 13435–13444).

Wohn, D. Y., Freeman, G., & McLaughlin, C. (2018). Explaining viewers' emotional, instrumental, and financial support provision for live streamers. In Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (pp. 1–13).

Xu X, Wu J H, Chang Y T, et al. The investigation of hedonic consumption, impulsive consumption and social sharing in e-commerce live-streaming video s[J]. 2019.